Free Lunch in Banking (preliminary) *

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Abstract

We found strong evidence of moral hazard in bank behavior under public loan guarantees, using a unique natural experiment in Japan during the COVID-19 pandemic. Specifically, exogenous variations in loan rates occurred randomly across 47 prefectures. This experiment was caused by the central government's so-called "zero-zero" loan program, intended at the time to save SMEs by providing 100% guarantees on bank loans and 100% reimbursement of interest expenses. The prefectural government arbitrarily set loan rate limits.

Keywords: moral hazard, cost screening, loan guarantee, Japan

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1 Introduction

We found strong evidence of moral hazard in bank behavior using a free lunch policy as a unique natural experiment in Japan during the COVID-19 pandemic. The so-called "zero-zero" loan program for small and medium enterprises (SMEs) provided 100% loan guarantees for eligible bank loans and 100% reimbursement of interest payments for SMEs. Although it is a central government backed policy, exogenous variations in loan rates occurred randomly across 47 prefectures at that time.

First, we found clear evidence of moral hazard. For banks with operations across multiple prefectures, loan growth is higher in prefectures with higher loan rate limits; by contrast, there is no such tendency among banks operating only in one prefecture. Note that, except for three megabanks, most banks in Japan are regional banks, concentrated in one or a few prefectures due to historical factors, including past bank licensing regulations across prefecture borders.

Second, we found evidence of costly screening behavior, which somewhat mitigates the moral hazard. In a prefecture with a low loan rate limit, banks tend to select bad firms more than good firms. By contrast, in a prefecture with a high loan rate limit, banks tend to select good firms more than bad firms. These two opposite behaviors are consistent with the costly screening hypothesis, which holds that screening occurs only if the benefits exceed the cost; otherwise, pooling occurs.

This within-prefecture behavior somewhat mitigates the across-prefecture moral hazard. Banks move their funds to high interest rate prefectures, where they select good firms. Still, the overall picture shows that banks increased loans to bad firms. Thus, this mitigating effect is not enough to cancel the moral hazard created by the free lunch policy.

Here, let us explain a bit about the free lunch policy. During the COVID-19 pandemic, the Japanese government supported SMEs, especially by providing almost free access to finance. Specifically, through the zero-zero loan program, SME bank loans were publicly

guaranteed. In the event of a firm's bankruptcy, the loan would be repaid to the bank by the Credit Guarantee Corporation. The 100 % guarantee has been in place since 2009, during the Global Financial Crisis. It was an increase from the 80% guarantees available before the GFC.

The Credit Guarantee Corporations had been charging a fee as an insurance premium. Under the zero-zero loan program during the COVID-19 pandemic, these fees were waived. Moreover, under this program, SMEs received full reimbursement of their interest payments from the government. In this sense, these loans were free for eligible SMEs and almost risk-free for banks.

Apparently, risky firms obtained more loans than safe firms (Hoshi et al., 2023). A criticism of this previous paper is that these weak firms indeed needed money to survive a supposedly temporary COVID-19 shock, and so the loans to weak firms were in line with the policy objective, even if they might not be supported by a conventional economic theory. In this paper, however, we provide stronger evidence of moral hazard that clearly runs counter to the policymakers' objective. Each prefecture is in charge of its Credit Guarantee Corporation, which is, however, backed by the central government budget. Each prefecture found it necessary to limit the bank loan rate for SMEs under the zero-zero loan program. Because interest expense is fully reimbursed for SMEs, there are strong incentives for banks to charge very high loan rates with little protest from SMEs. We find that the loan rate limits appear random across prefectures. This randomness under the same central government policy creates a rare natural experiment that allows us to identify distortive bank behaviors.

2 "Zero-Zero" Loan Program

The zero-zero loan program is the official name of a special concessional loan program known as "effective zero interest loans without collaterals" and it was one of the main support measures to SMEs provided by the Japanese government during COVID-19.

This program makes bank loans to SMEs risk-free, as interests are paid essentially by the government and the principals are 100% guaranteed. The special concessional loan programs were offered by state-owned banks and by private sector banks.[1] Applications for these loans were allowed during 2020 fiscal year, that is, until the end of March 2021. This study focuses on this "effective zero interest loans without collaterals" provided by private sector banks.

The zero-zero loan program uses the Credit Guarantee Corporations, which are public institutions established in all prefectures and have been financially backed by the central government.[2] The eligibility conditions for the zero-zero loan program were more lenient than those for standard programs provided by the Credit Guarantee Corporations. First, SMEs were allowed to apply for and receive zero-zero loans without collateral if their monthly sales had declined by 5% or more compared with the same period in the previous year due to COVID-19.[3] Moreover, the guarantee fee, which is normally around 1%, was cut to zero for SMEs whose sales had decreased by 15% or more and eligible small businesses, and cut in half for other eligible SMEs.

Most importantly, the guarantee was 100% for SMEs whose sales dropped by 15% or more. In Japan, bank loans for SMEs with 80% loan guarantee from Credit Guarantee Corporations have been widely used since 2007. On the other hand, there have been special bank loan programs with 100% loan guarantee since 2009.[4] Loan programs with a 100% loan guarantee were supposed to be gradually phased out after 2019, but in response to the COVID-19 pandemic, the government fully reintroduced this special scheme to help banks provide loans to SMEs smoothly.

Furthermore, SMEs with 15% or more sales drop due to COVID-19 were able to

[1]Initially, in March 2020, only the former provided the program immediately after the COVID-19 pandemic occurred. However, due to increasing demand for loan applications, the special loan program by private sector banks was introduced in May 2020.

[2]All the Credit Guarantee Corporations receive financial backstop by the Japan Finance Corporation, which is a central government agency.

[3]To be precise, firms needed to be approved for specific facilities set by the central government, that is, the Safety Net Guarantee No.4, No.5, or the Crisis-related Guarantee.

[4]Special loan programs for SMEs introduced after the Great Financial Crisis and extended due to the Great East Japan Earthquake in 2011.

receive 100% reimbursement of interest payments. For loans to those SMEs, a government entity called the Organization for Small & Medium Enterprises and Regional Innovation provided a subsidy equivalent to up to three years' worth of interest expenses.[5] As a result, SMEs severely affected by COVID-19 were able to obtain loans with no financial burden. Small businesses and SMEs experiencing a sales decline of at least 15% qualified for this most generous treatment. This program is a free lunch for an eligible SME. For banks, providing a free lunch is profitable. However, profitability varies with prefectures. The loan rates under the zero-zero loan program were determined by prefectural governments, and they varied with prefectures. Some prefectures fixed the interest rates, while others set the upper limits or caps of loan rates. Moreover, several prefectures introduced multiple interest rate criteria depending on factors such as the degree of the sales decline due to the COVID-19 shock and the length of the loan maturity. Banks determined their loan rates based on these standards set by the prefecture in which they extended loans to SMEs under the zero-zero loan program.

There exists substantial heterogeneity in the interest rate controls across 47 prefectures. Table 1 presents detailed information. 17 prefectures adopted a fixed interest rate that did not depend on borrower characteristics. In addition, 9 prefectures adopted an interest rate cap while still keeping the interest rate independent of borrower characteristics. In the other prefectures, multiple interest rate criteria were set depending on the degree of sales decline due to COVID-19 and loan maturity, which was different from whether the prefecture adopted a fixed interest rate or an interest rate cap. In this study, we classify the 21 prefectures highlighted in red as prefectures with fixed interest rates, and the remaining 26 prefectures highlighted in blue as prefectures with interest rate caps.[6]

[5]The Organization for Small & Medium Enterprises and Regional Innovation provided subsidies to each prefectural government, and each government subsidized interest payments to financial institutions. Since this organization operates under the jurisdiction of the central government, this reimbursement of interest payments can be regarded as financed by the central government.

[6]Because we focus on firms that experienced a sales decline of at least 15%, the interest rate on zero-zero loans is uniquely identified in prefectures that adopted a fixed interest rate and multiple criteria contingent on only the degree of sales decline. By contrast, in prefectures where fixed interest rate criteria depend on loan maturity, banks can flexibly set interest rates through the choice of loan maturity. We therefore treat the latter prefectures as having interest rate caps rather than fixed interest rates.

Table 1: Interest Rate Criteria Classification

	no criteria	sales-only criteria (15% or more sales decline or not)	loan-maturity-only criteria (less than 3 years etc.)	both sales and loan maturity criteria	others	total
set fixed rates	17	3	7	2	1	30
set caps	9	4	1	3	0	17
total	26	7	8	5	1	47

Notes: This table shows the classification of prefectural interest rates under the zero-zero loan program depending on two perspectives: whether fixed rates are set or caps are set, and whether the interest rate setting is common for all borrowers or the interest rate settings are various depending on the scale of borrowers' damage by COVID-19, the length of their loan maturity, and so on. The table is constructed by the authors using information available on each prefecture's website.

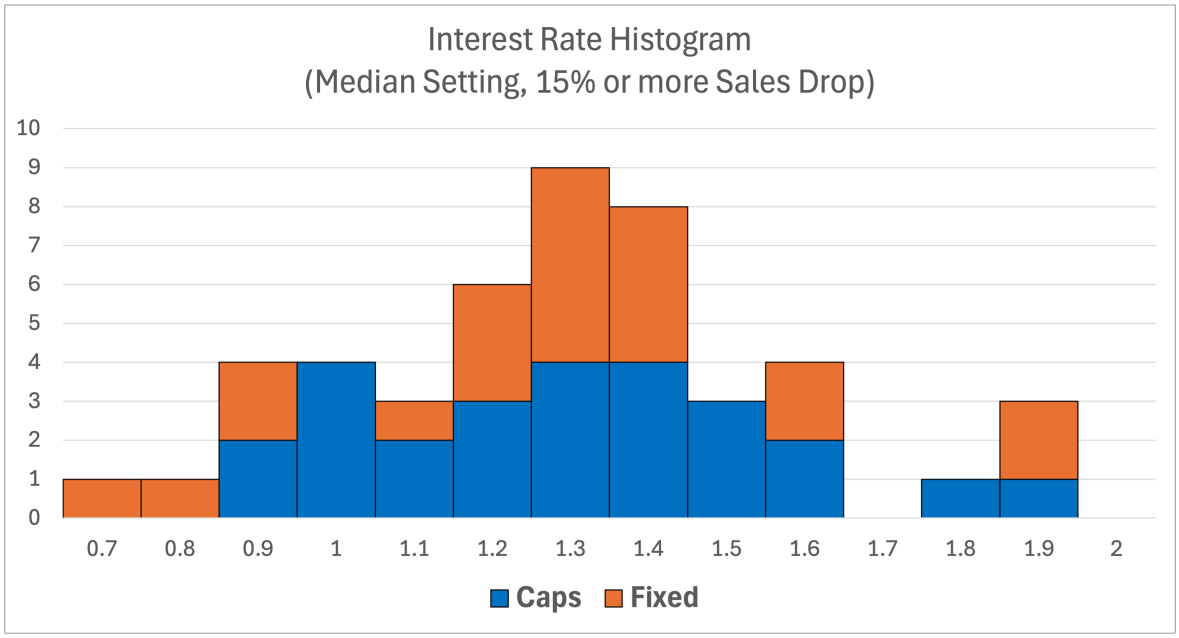
Figure 1 shows histograms of the loan rates in each prefecture under the zero-zero loan program. They varied substantially across prefectures. Note that the figure focuses on firms that experienced a sales decline of 15% or more, for which the loan guarantee was 100%. Also, we use the median of the highest value and the lowest value among all candidates in prefectures with multiple criteria depending on loan maturity.[7] The blue part represents the number of prefectures with interest rate caps, while the orange part shows the number of prefectures with the fixed interest rate.

After investing a large number of documents and many interviews with related practitioners, it still remains for us unclear why, under the zero-zero loan program, the specific interest rate levels or criteria were chosen in each prefecture. In fact, we know that in many prefectures, the interest rate controls under the zero-zero loan program follow those used in special loan programs implemented in response to natural disasters, such as the Great East Japan Earthquake. However, for these disaster-related programs, there was again no information available on why the specific interest rate levels or criteria were chosen.

Here, we show the randomness of the interest controls across prefectures. Figure 2 and 3 show the correlations between interest rate levels and GDP per capita and GDP

[7]For prefectures that have only a single interest rate standard, the interest rate is used across all settings. In prefectures that have an upper limit on the interest rate, we use the upper-limit value. Since zero-zero loans have almost no lending risk for financial institutions, lenders had an incentive to set interest rates as high as permitted to maximize their profits.

Figure 1: Interest Rate Histogram by Prefecture



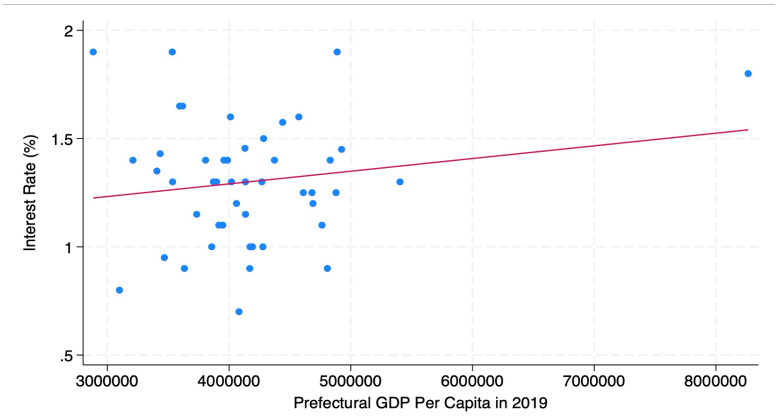
Notes: This figure shows the histogram of prefectural interest rates under the zero-zero loan program. We use the interest controls assigned to firms with 15% or more sales drop due to the COVID-19 shock. The orange one is the histogram of interest rates of prefectures with fixed rates, while the blue one is the histogram of interest rates of prefectures with caps. The figure is constructed by the authors using information available on each prefecture's website.

growth for each prefecture, respectively. Figure 4 shows the relationship between the average corporate loan rate in each prefecture and the prefectural interest rate controls under the zero-zero loan program.[8] Figure 5 shows the correlation between interest rate controls and the loan market concentration measure, the Herfindahl-Hirschman Index (HHI), for each prefecture.[9] In all figures, the interest rate controls by prefectures on the vertical axis correspond to those shown in Figure 1, namely the interest rates assigned to firms with a sales decline of 15% or more. The horizontal axes report each economic indicator measured before the COVID-19 pandemic.

[8]The average corporate loan rate is calculated using firm-level data on interest-bearing debt and interest payments obtained from Tokyo Shoko Research (TSR) financial statement data. Note that TSR is one of the major Japanese credit rating agencies and possesses detailed financial and related information for Japanese firms, including SMEs. We use the most recent fiscal-year (2019) data before the COVID-19 pandemic. Interest-bearing debt is defined as the sum of short-term borrowings, long-term borrowings, and corporate bonds.

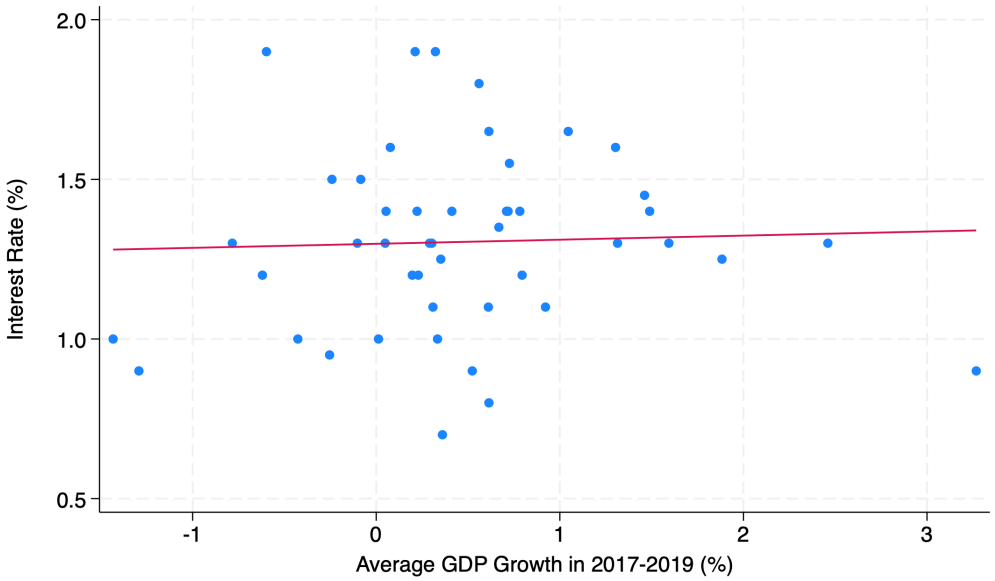
[9]We use prefecture-level HHI values calculated by Uesugi et al. (2024). The HHI is a commonly used measure of market concentration. When the prefectural HHI approaches zero, it indicates that many financial institutions operate in the prefecture and the loan market is close to perfect competition. Conversely, as the HHI is away from zero and approaches 10,000, it implies that fewer financial institutions operate in the prefecture and that the lending market is closer to a monopoly. It is well known that this prefectural HHI is positively correlated with the average loan rate in each prefecture.

Figure 2: Correlation between Interest Rate and Prefectural GDP Per Capita



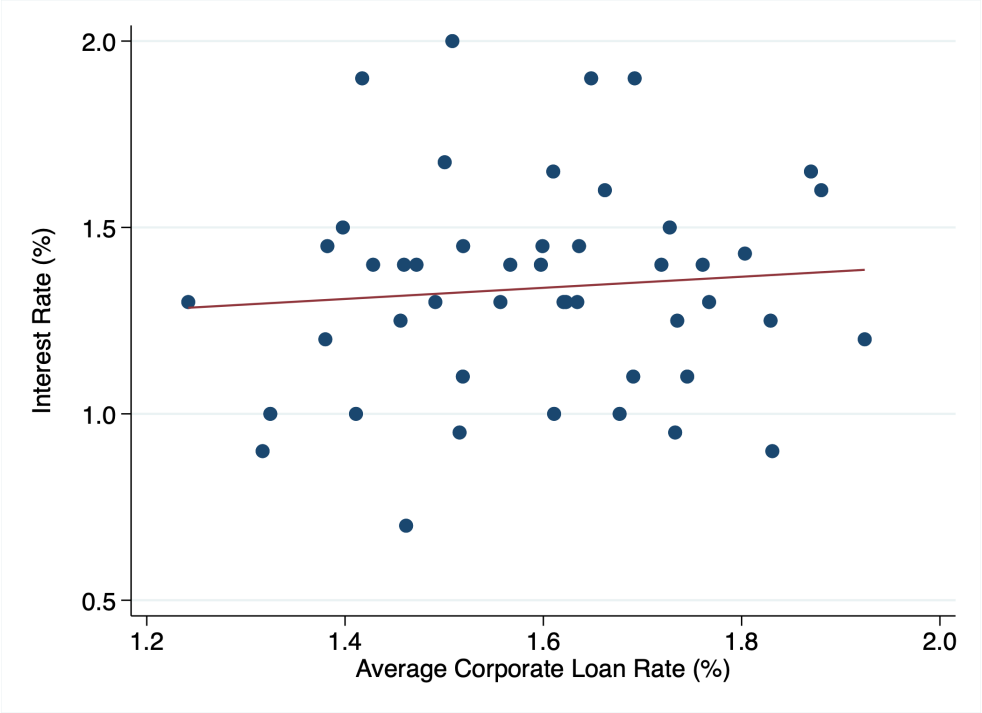
Notes: This figure shows the correlation between prefectural interest rates under the zero-zero loan program and the prefectural GDP per capita in 2019. Data of prefectural GDP per capita in 2019 is referred from the Cabinet Office's Prefectural Accounts. Prefectural interest rates used are same as those explained in Table 1 and Figure 1.

Figure 3: Correlation between Interest Rate and Prefectural GDP Growth



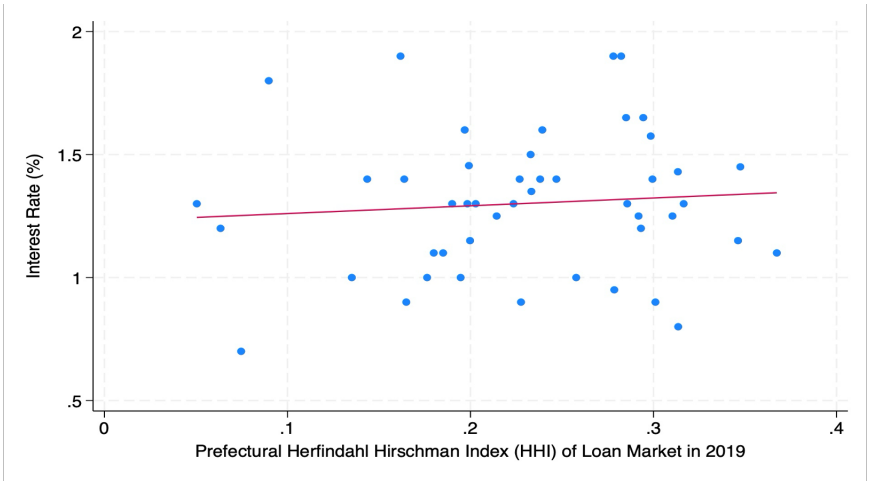
Notes: This figure shows the correlation between prefectural interest rates under the zero-zero loan program and the average prefectural GDP growth in 2017-2019. The prefectural GDP growth in 2017-2019 is calculated by the authors. Data of prefectural GDP growth in each year is referred from the Cabinet Office's Prefectural Accounts. Prefectural interest rates used are the same as those explained in Table 1 and Figure 1.

Figure 4: Correlation between Interest Rate and Average Corporate Loan Rate



Notes: This figure shows the correlation between prefectural interest rates under the zero-zero loan program and the average corporate loan rate in 2019. The average corporate loan rate is calculated by the authors using firm-level data on interest-bearing debt and interest payments obtained from TSR financial statement data. Prefectural interest rates used are the same as those explained in Table 1 and Figure 1.

Figure 5: Correlation between Interest Rate and HHI in Loan Market



These figures show no prefectural-level correlation between the interest controls and prefectural GDP per capita, GDP growth rates, average corporate loan rates, or HHI.[10] Also, Table 2 shows the results of regressions of the controlled interest rates on these variables, confirming no correlations. Overall, we are certain that interest controls under the zero-zero loan program are randomly assigned across prefectures.

Table 2: simple regression about measures related to GDP and HHI

	(1) Interest Rate	(2) Interest Rate	(3) Interest Rate	(4) Interest Rate
GDP per capita in 2019	0.000			
	(0.000)			
Average GDP growth in 2017-2019		0.000		
		(0.000)		
Average corporate loan rate in 2019			0.149	
			(0.260)	
HHI of loan market in 2019				0.317
				(0.561)
Observations	47	47	47	47

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

3 Data Description

There are two main data sets used in this study: the results of our own firm-level survey jointly designed and conducted with TSR, and the firm-level credit report and financial statement data provided by TSR. The firm coverage of the data is considered as the best among Japanese firm-level financial databases, except for a legally binding census, which, however, provides very limited financial information of firms once every five years.

Our original firm survey was conducted twice. The first survey was conducted in October 2021 by Hoshi, Kawaguchi, and Ueda, who is one of the coauthors of this paper. The survey asked firms whether they applied for and received government support programs, including the zero-zero loan program, as well as about the impact of COVID-19 on their business conditions. The results of the survey were already used in Hoshi

[10]We also confirm that prefectural interest controls are not correlated with other major economic indicators. Details are provided in Appendix 1.

et al. (2023). The second survey was conducted by the two authors of this paper in May 2024. This survey focused specifically on the zero-zero loan program and collected detailed information, in particular, on their repayment status at the time of the survey. Both surveys were conducted by inviting TSR's email magazine subscribers to respond. In total, we obtained responses from 7,166 firms from the two surveys.

The firm-level credit rating data and financial statement data compiled by TSR also contain firm characteristics, such as year of establishment, headquarters location, industry classification defined by main products and services, number of employees, and main banks, from which a firm borrows mainly. Following the approach in Hoshi et al. (2023), we use the data at the end of 2019 as the pre-COVID-19 pandemic information.

For bank balance sheet information, we use two datasets: Financial Statements of All Banks published by the Japanese Bankers Association and Nikkei NEEDS FinancialQUEST. These datasets provide annual balance sheet information for Japanese city banks, regional banks, and credit unions (Shinkins). From these data, we compute each bank's average non-performing loan (NPL) ratio and average capital adequacy ratio over the three years immediately before the COVID-19 pandemic, and use them as measures of bank risk. We merge these bank-level variables with firm-level survey data using information on firms' main banks to examine the relationship between pre-pandemic lenders' risk and their lending behavior under the zero-zero loan program.

Figure 6 illustrates the composition of firms included in our analysis. Among the 7,166 survey respondents, 2,169 firms were able to be matched with credit report and financial statement data and satisfied the eligibility conditions for the zero-zero loan program. Of these, 1,689 firms met the criteria for both a 100% loan guarantee and full reimbursement of interest payments. We define this group as our main analysis sample.

Figure 7 classifies firms in the main sample according to the type of their main banks. Private sector banks in Japan are broadly categorized into city banks operating nationwide and regional banks.[11] Among regional banks, some operate in multiple prefectures,

[11]We omit analyses on other regional financial institutions, which consist mainly of credit unions and

while others operate only within a single prefecture. Figure 7 shows that, among the main sample, 476 firms had city banks as their main banks, while 1,211 firms had regional financial institutions. Of the latter firms, 917 firms were associated with banks operating in multiple prefectures, and 294 firms with banks operating within a single prefecture. For 2 firms, information on the main bank was unavailable.

Figure 6: Sample Classification

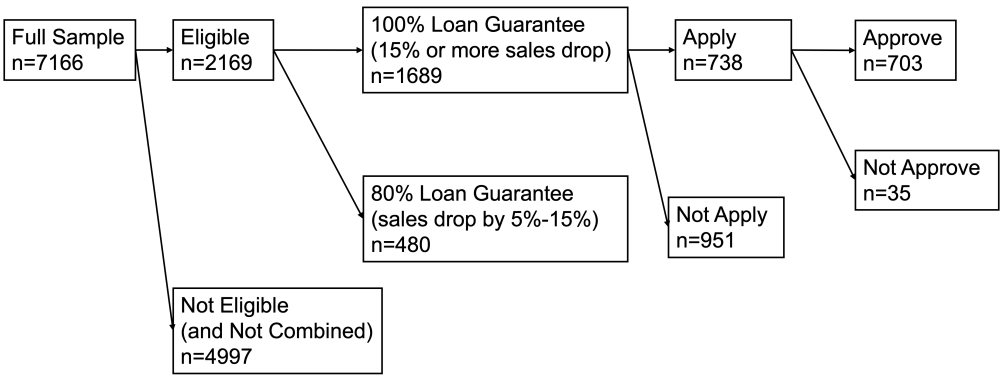
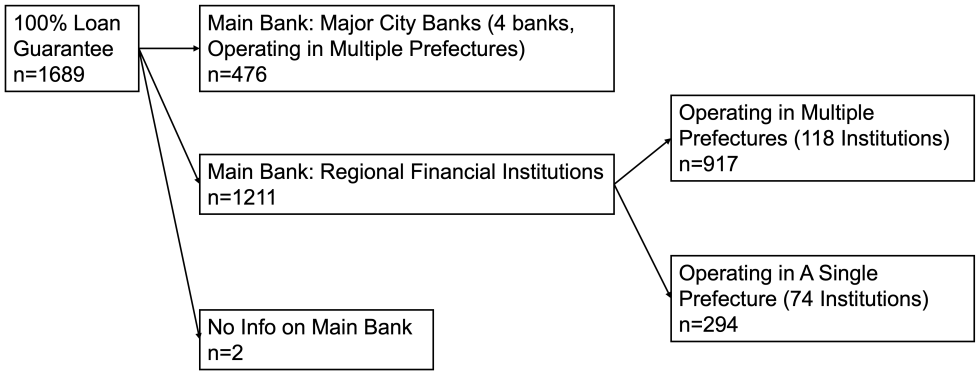


Figure 7: Sample Classification by Main Bank



We focus on the zero-zero loan approval as the outcome variable representing bank lending behavior. As shown in Figure 6, the number of firms that applied for zero-zero loans was almost the same as those that were approved. This may raise a question whether the number of approvals reflects bank lending decisions or firm borrowing behavior. In our survey, we ask if the firm formally applied for the zero-zero loans. In practice, however, firms usually have to go through pre-approval processes, and only those allowed by banks can apply for loans. Hence, by the time an application was formally submitted, it was already expected that the application would be approved. Here, we do not have the

credit cooperatives.

true loan demand that should include all those firms that went through pre-approved processes.[12] In the end, we regard the loan approval as the lending decision of the bank facing many loan applications.

The most important explanatory variable in our analysis is the prefectural interest controls under the zero-zero loan program. As discussed above, the ways to control loan rates vary among prefectures, and thus we assign a specific interest rate to each prefecture. We surmise that lenders choose the highest interest rate in prefectures with the interest rate caps. Then, we construct three prefectural interest rate representations: high, low, and median. For prefectures with multiple interest rate criteria often depending on loan maturity, the highrate picks the highest rate among all upper limit rates, while the low rate uses the lowest one. The median uses the median of the two.[13] In our main analysis, we primarily use the median.

Another key variable is the default score, which measures the firm-level default risk. We construct the default score using firms' credit scores as of the end of 2019. This credit score is the TSR's most valuable product, which gauges firm creditworthiness based on performance, management characteristics, and growth prospects. We construct the default score at the end of 2019, before COVID-19, by subtracting each firm's credit score from 100 and dividing by 100 to take a value between 0 and 1. While a higher credit score indicates lower risk, a higher default score corresponds to higher default risk.

We find that the default score is an effective measure of the default risk during and after COVID-19. While we would like to know the riskiness of firms expected before the COVID-19 pandemic, the default score at end-2019 might not reflect the true default risk during and after the COVID-19 pandemic, which was an unprecedented big shock. This worry turns out unfounded. Figure 8 plots the percentage of firms that have not repaid

[12]Another possible factor is that firms that applied for zero-zero loans but were not approved may have been less likely to respond to the survey. Because the survey was conducted by the major credit rating agency, firms may have been concerned that their true answers could negatively affect their credit ratings and future business prospects. Such concerns may have contributed to the similarity between the number of applications and approvals observed in the survey data.

[13]In prefectures where a specific interest rate is set regardless of the degree of sales decline or loan maturity, the same interest rate is assigned as the high, low, and median.

Figure 8: Correlation between Default Score in 2019 and Probability of Not Repaying as Scheduled

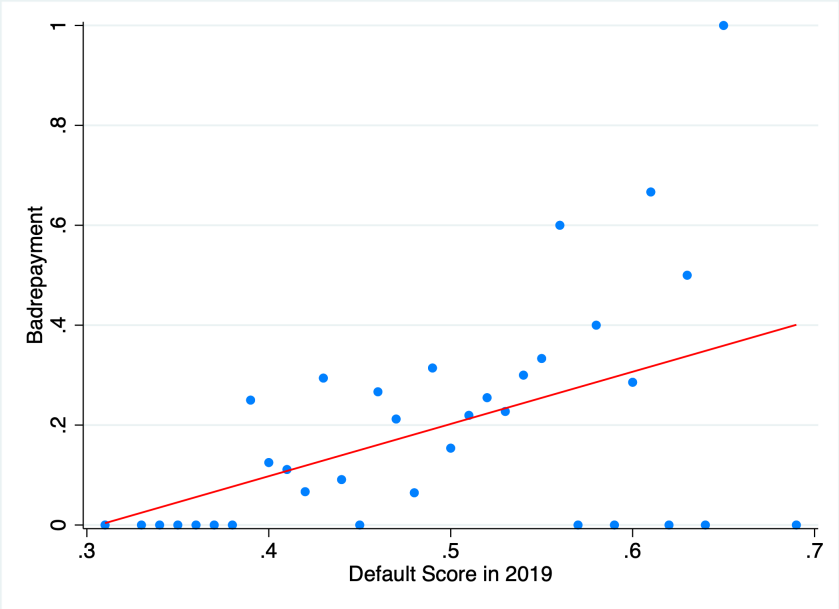


Figure 9: Distribution of Default Score

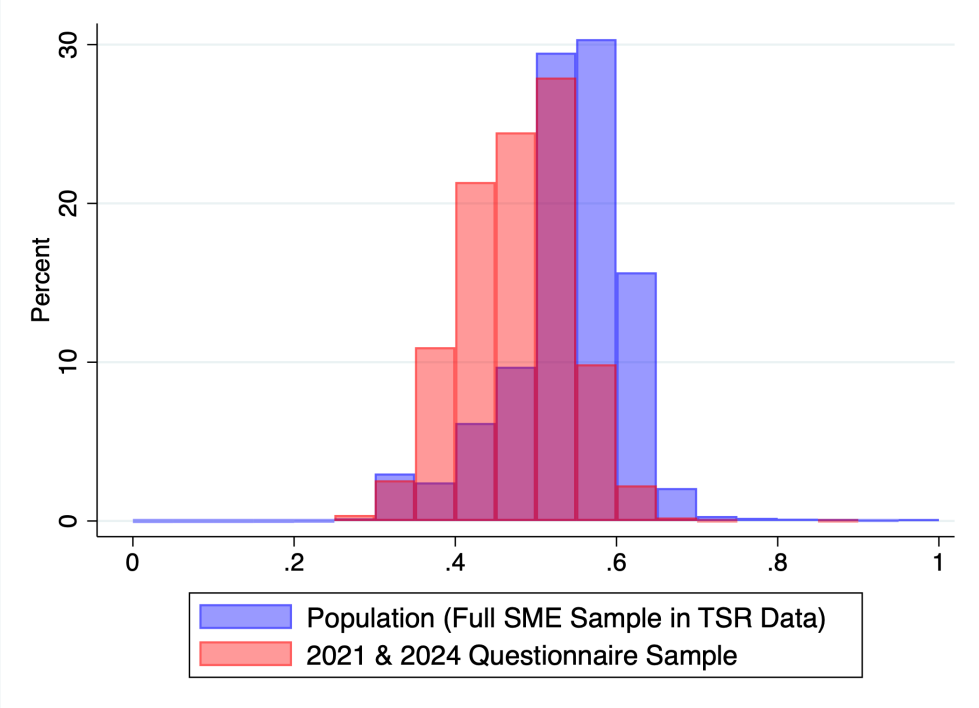
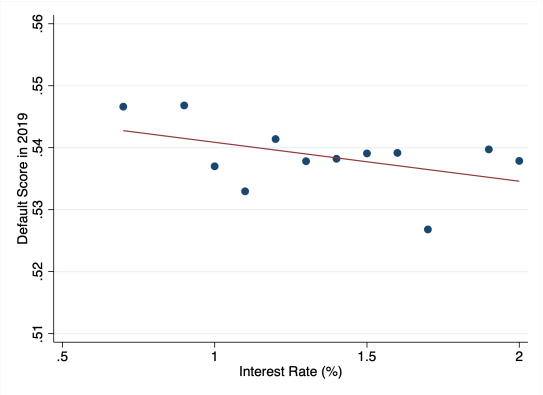
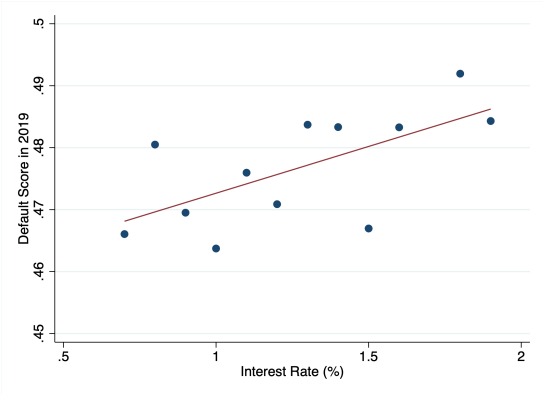


Figure 10: Correlation between Interest Rate and Default Score



TSR Full SME Sample



2021 & 2024 Questionnaire Sample

their zero-zero loans as scheduled by each value of default score, showing the correlation between the default score and the bad repayment status of zero-zero loans.[14] The higher the default score is, the higher the percentage of firms that faced troubles with repaying zero-zero loans by May 2024 is.

To better understand sample characteristics, we compare the survey sample with TSR's full database as of the end of 2019.[15] Figure 9 shows the distribution of default score, revealing that the survey sample is skewed toward lower risk firms compared to the full TSR sample. Figure 10 plots the relationship between default score and prefectural interest rates under the zero-zero loan program. The left panel shows this relationship for the survey sample, while the right panel shows it for the full TSR sample. Unlike the full sample, the survey sample exhibits a somewhat positive relationship between default score and interest rates. This indicates that, relative to the overall SME population, the survey sample contains a higher proportion of lower risk firms and fewer high risk firms. Because the default score is a crucial variable in our analysis, we address this sampling bias by reweighting in the regressions, so that the distribution of default score in the survey sample matches that of the full sample. Table 3 reports descriptive statistics for all variables, and Table 4 presents the correlation matrix.

[14] In the survey conducted in 2024, we asked whether repayment had been completed, whether repayment terms had been changed, and whether refinancing or other loan programs were used for the repayment. Here, we classify firms that have not completed the repayment and changed repayment terms or used refinancing programs or other loans for repayment as firms that encountered repayment troubles.

[15] In this comparison, we restrict the TSR database to SMEs as defined by the Small and Medium-sized Enterprise Basic Act.

Table 3: Descriptive Statistics

Variables	Explanation	N	mean	SD
Bankapprove	Binary variable that takes 1 if a firm was approved for "zero-zero" loan.	1,689	.416	.493
Interest Rate	Interest rates of the "zero-zero" loan policy set in each prefecture. The median is taken if there is a range of interest rates.	47	1.337	.286
Defaultscore_2019	Credit score is the main product TSR offers. We calculate "100 - credit score" and normalize it to evaluate firms' risk in 2019. (Good 0.0 – Bad 1.0).	1,689	.467	.060
Employee_2019	The number of employees of a firm in 2019.	1,689	49.404	58.820
Sales_2019	Sales of a firm in 2019. (thousand yen)	1,688	2352330	5537191
Cash-to-Assets_2019	The ratio of cash and deposits to total assets for each firm in 2019.	1,689	.227	.159
CurrentAssets_2019	The ratio of current assets to total assets for each firm in 2019.	1,689	.622	.213
2016-2018 Ave. NPL ratio	The average of non-performing loan ratio of each financial institution among 2016-2018.	199	3.417	2.137
2016-2018 Ave. capital ratio	The average of capital ratio of each financial institution among 2016-2018.	208	12.263	5.297

Table 4: Correlation Table

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) Bankapprove	1.000								
(2) Interest Rate	-0.012	1.000							
(3) Defaultscore_2019	0.133	0.128	1.000						
(4) Employee_2019	-0.142	0.028	-0.376	1.000					
(5) Sales_2019	-0.156	0.057	-0.315	0.438	1.000				
(6) Cash-to-Assets_2019	-0.015	0.037	-0.035	-0.148	-0.160	1.000			
(7) CurrentAssets_2019	-0.145	-0.077	-0.357	-0.020	-0.040	0.472	1.000		
(8) 2016-2018 Ave. NPL ratio	-0.110	-0.075	-0.367	-0.061	-0.074	-0.007	0.738	1.000	
(9) 2016-2018 Ave. capital ratio	0.068	0.029	0.026	0.017	-0.004	0.008	-0.060	-0.037	1.000

4 Benchmark Estimation

4.1 Methodology

We examine how variations among prefectural interest rates affected the bank lending behavior under the zero-zero loan program. Our analysis focuses on firms that experienced 15% or more monthly sales decline immediately after the COVID-19 pandemic to examine the lending behavior of private banks in loans with 100% public loan guarantee and 100% reimbursement of interest payments.

We investigate whether bank lending behavior was affected by prefectural interest controls by comparing banks that operate in multiple prefectures with those that operate

in only a single prefecture. We predict that banks operating in multiple prefectures engage in arbitrage behavior by exploiting differences in prefectural interest controls. Also, we focus on firm default risk. We examine whether differences in prefectural interest controls generated distortions in credit allocation across firms with varying default risks.

As the dependent variable, we use a binary variable that equals one if a firm's zero-zero loan was approved and zero otherwise. Firms that did not apply for a zero-zero loan are included in the sample, and their binary variable takes zero. As the main explanatory variable, we use the prefectural interest rate measure, the median for the benchmark analysis. We estimate its effect on whether the zero-zero loan was approved.

We further include the squared term of the prefectural interest rate, as well as an interaction term between the prefectural interest rate and each firm's default score measured before COVID-19. The coefficients on the square term and interaction term allow us not only to capture nonlinear effects of interest rates on bank lending decisions, but also to examine how the impact of interest rates varies with borrower default risk.

We also include each bank's non-performing loan (NPL) ratio and capital adequacy ratio as explanatory variables to examine how their balance sheet conditions before COVID-19 affected their lending behavior. For the NPL ratio and capital adequacy ratio, we use the average values over fiscal years 2016-2018. We exclude fiscal year 2019 because it includes the period up to March 2020, which overlapped with the onset of the COVID-19 pandemic.

We estimate the fixed effect model and control for heterogeneity of industries and main banks, using the industry fixed effects based on the three digit industry classification and the main bank fixed effects. In addition, we include firms' pre-pandemic sales, numbers of employees, cash-to-asset ratio, and liquid asset ratio as control variables to account for differences in firm size and financial constraints before COVID-19.

As discussed in the previous section, the analysis sample consists of survey respondents and is therefore not randomly drawn. In particular, the distribution of default scores

differs from that of the full population of SMEs in the TSR credit report data. To correct for this sampling bias, we reweight all estimations so that the distribution of default scores in the analysis sample matches that shown in Figure 9.

The weighted regression with fixed effects is specified as follows.

$$
\begin{aligned}
Y_{i,j,k,b,2020} = {} & \beta_1 IR_{k,2020} + \beta_2 DefaultScore_{i,j,k,b,2019} + \beta_3 (IR_{k,2020} \times DefaultScore_{i,j,k,b,2019}) \\
& + \beta_4 IR^2_{k,2020} + \beta_5 (IR^2_{k,2020} \times DefaultScore_{i,j,k,b,2019}) + \beta_6 \ln (Sales)_{i,j,k,b,2019} \\
& + \beta_7 \ln (Emp)_{i,j,k,b,2019} + \beta_8 CashtoAssets_{i,j,k,b,2019} \\
& + \beta_9 CurrentAssets_{i,j,k,b,2019} + Industry_j + MainBank_b + u_{i,j,k,b,2020}
\end{aligned}
$$

where $Y_{i,j,k,b,2020}$ indicates the dependent variable of firm i explained above, $IR_{k,2020}$ is the interest rate measure of the zero-zero loan program set in each prefecture k explained above, $DefaultScore_{i,j,k,b,2019}$ is the default score of firm i in 2019, $\ln (Sales)_{i,j,k,b,2019}$ is the natural logarithm of the amount of sales in 2019, $\ln (Emp)_{i,j,k,b,2019}$ is the natural logarithm of employment in 2019, $CashtoAssets_{i,j,k,b,2019}$ is the amount of cash holding in 2019 to total asset ratio, $CurrentAssets_{i,j,k,b,2019}$ is the amount of current asset to total asset ratio of firm i in 2019, $Industry_j$ is the industry fixed effect, and $MainBank_b$ is the main bank fixed effect.

4.2 Estimation Results

Table 5 reported the estimation results for banks operating in multiple prefectures. In column (1), none of the coefficients were statistically significant. In contrast, column (2) showed that the estimated coefficient on the interest rate was significantly positive. This result implied that banks operating across multiple prefectures were more likely to extend zero-zero loans in prefectures with higher interest rates. Facing multiple interest rates, these banks appeared to arbitrage by allocating more loans to prefectures with high interest rates.

Table 5: Estimation Results of Financial Institutions Operating in Multiple Prefectures

	(1)	(2)	(3)
	bank approve	bank approve	bank approve
Interest Rate	0.023	1.097**	-5.073*
	(0.072)	(0.447)	(2.730)
Defaultscore_2019	0.032	3.094**	-6.391
	(0.347)	(1.383)	(4.169)
Interest Rate * Defaultscore_2019		-2.243**	11.775*
		(0.972)	(6.121)
Interest Rate^2			2.200**
			(1.003)
Interest Rate$^2 * Defaultscore$_2019			-4.978**
			(2.212)
Cash-to-Assets_2019	-0.111	-0.120	-0.117
	(0.144)	(0.142)	(0.142)
CurrentAssets_2019	0.051	0.059	0.053
	(0.103)	(0.103)	(0.102)
Sales_2019	-0.022	-0.028	-0.030
	(0.027)	(0.024)	(0.023)
Employees_2019	-0.002	0.000	0.001
	(0.027)	(0.026)	(0.025)
Observations	1301	1301	1301
Interest Rate Setting	Median	Median	Median
Industry FE	YES	YES	YES
Mainbank FE	YES	YES	YES

Notes: Robust standard errors clustered at the prefectureindustry level are reported in parentheses, where industries are defined at the three-digit level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

At the same time, the estimated coefficient on the interaction term between the interest rate and the default score was significantly negative. Relative to the positive coefficient on the interest rate itself, this result implied that when the borrowers' default score exceeded approximately 0.5, they did not lend to them in prefectures with high interest rates. Furthermore, column (3) showed that the coefficient on the squared term of interest rate was significantly positive, while the coefficient on the interaction between the interest rate square and the default score was significantly negative. These results reinforced the finding that, although lending under the zero-zero loan program increased in prefectures with higher interest rates, this pattern was driven primarily by firms with low default risk, whereas the opposite pattern emerged for those with high default risk.

Table 6 shows the estimation results for approvals of zero-zero loans by financial

Table 6: Estimation Results of Financial Institutions Operating in a Single Prefecture

	(1)	(2)	(3)
	bank approve	bank approve	bank approve
Interest Rate	0.050	-0.489	7.890
	(0.185)	(1.225)	(8.538)
Defaultscore_2019	0.183	-1.171	7.272
	(0.847)	(3.251)	(10.924)
Interest Rate * Defaultscore_2019		1.087	-12.381
		(2.516)	(17.126)
Interest Rate^2			-3.182
			(3.270)
Interest Rate$^2 * Defaultscore$_2019			5.131
			(6.529)
Cash-to-Assets_2019	-0.111	-0.109	-0.129
	(0.377)	(0.379)	(0.396)
CurrentAssets_2019	0.089	0.088	0.118
	(0.269)	(0.270)	(0.269)
Sales_2019	0.069	0.068	0.073
	(0.074)	(0.074)	(0.074)
Employees_2019	-0.138	-0.135	-0.139
	(0.088)	(0.089)	(0.089)
Observations	225	225	225
Interest Rate Setting	Median	Median	Median
Industry FE	YES	YES	YES
Mainbank FE	YES	YES	YES

Notes: Robust standard errors clustered at the prefectureindustry level are reported in parentheses, where industries are defined at the three-digit level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

institutions operating in only a single prefecture, showing no evidence of moral hazard. Column (1) presents the specification without interaction terms, column (2) adds the interaction term between the prefectural interest rate and the firm's default score, and column (3) further adds the squared term of the prefectural interest rate.

In column (1), while the estimated coefficient on the default score was significantly positive, the coefficient on the interest rate was not statistically significant. In columns (2) and (3), none of the estimated coefficients was statistically significant. These results indicated that, for banks operating in only one prefecture, lending behavior under the zero-zero loan program did not differ systematically with respect to prefectural interest controls.

4.3 Empirical Results for (Non-)Screening

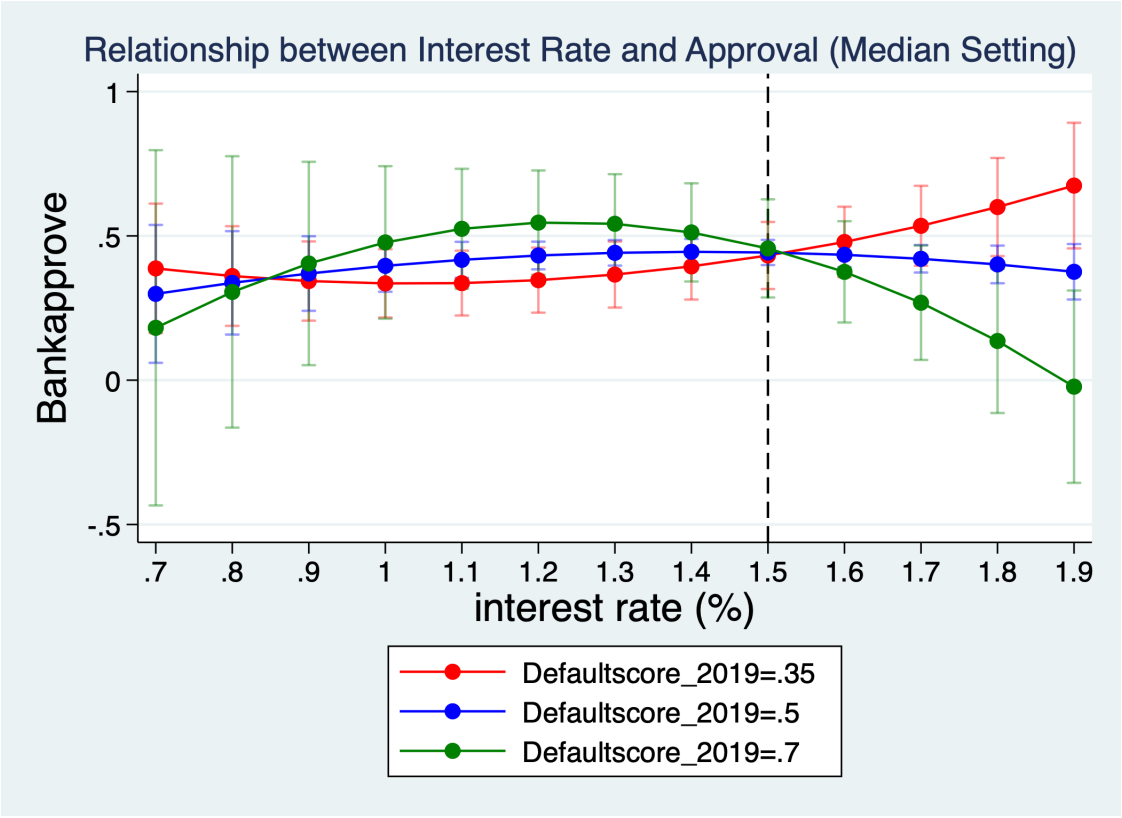
To provide a more intuitive interpretation of the interaction term, we examined the relationship between loan rates and approval probabilities conditional on borrower default risk using plots. Figure 11 plotted the fitted values of the dependent variable from the specification in column (3) against the interest rate, separately for different levels of default risk.[16] The green line corresponded to a low risk borrower with a default score of 0.35, the blue line corresponded to a borrower with a default score of 0.5, and the red line corresponded to a high risk borrower with a default score of 0.7.[17] For low risk borrowers, the relationship was upward sloping, which implied that they were more likely to be approved in prefectures with higher interest rates. As borrower risk increased, the slope became flatter and eventually turned negative. For high risk borrowers, the relationship was clearly downward sloping. These patterns were fully consistent with the estimated coefficients on the interaction terms.

The figure indicated that, in prefectures with sufficiently high interest rates, banks extended more zero-zero loans to borrowers with low default risk. In contrast, in prefectures with interest rates below a certain threshold, no statistically significant difference was observed in approval across borrower risk levels. Although zero-zero loans had 100% interest reimbursement for up to three years, they may not be entirely risk-free for lenders. If a borrower went bankrupt before maturity, the lender's revenue from interest was reduced. As a result, financial institutions operating across multiple prefectures appeared to have allocated more funds to prefectures with high interest rates and, even at some cost of screening, chose safer borrowers to minimize risk while maximizing returns. Conversely, in prefectures with low interest rates, weaker incentives to cover screening costs appeared to have led to inappropriate screening and lending loans regardless of firm's default risk. These findings were consistent with the theoretical predictions of Gao and Ueda (2025),

[16] All variables other than the default score and the interest rate are fixed at their sample means when computing the fitted values.

[17] According to Tokyo Shoko Research (TSR), firms with the default score below 0.35 are classified as low risk ones, those with scores between 0.35 and 0.5 as medium-risk ones, those between 0.5 and 0.7 as moderately high risk ones, and those above 0.7 as high risk ones. Therefore, we use these three cutoff values as thresholds in the analysis.

Figure 11: Relationship between Approval and Interest Rates

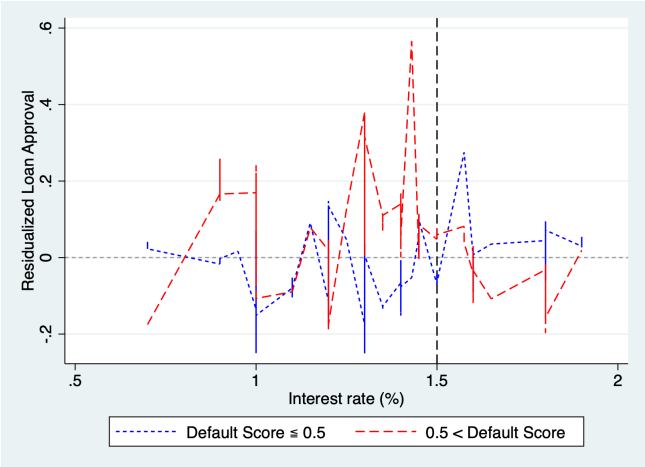


which showed that when interest rates were sufficiently high, lenders select only good firms, whereas in low interest rate environments, lenders do not distinguish firm types, which led to a pooling equilibrium.

We present additional evidence using nonparametric estimation to show the relationship of prefectural interest rates and banks' lending behavior depending on borrowers' default score. Figure 12 illustrates the relationship between the lending behavior of banks operating in multiple prefectures, prefectural interest rates, and borrowers' default risk using nonparametric local regression. Specifically, we remove the effects of other variables from the binary variable on the loan approval and visualize the relationship between the resulting residuals and prefectural interest rates.[18] In this figure, the sample was divided into two groups based on whether the default score was below or above 0.5, and the relationships were plotted separately for each group.

[18]Details of the nonparametric local regression procedure used for this visualization, as well as corresponding plots for financial institutions operating in a single prefecture, are explained in Appendix 4.

Figure 12: Relationship between Approval and Interest Rates Using Local Regression



Note: The figure plots locally weighted linear regressions estimated using a tri-cube kernel, as implemented by the "lowess" command in Stata, with a bandwidth of 0.05.

The figure revealed a clear difference in patterns depending on whether the interest rate was above or below 1.5%. Specifically, when interest rates exceeded 1.5%, banks were more likely to extend more loans to low risk firms, and vice versa. The patterns observed in Figure 12 were consistent with the regression results of Table 5. In Figure 11, we found that in prefectures with relatively not high interest rates, there was no statistically significant difference in the approval of zero-zero loans depending on firm's risk. In contrast, the nonparametric local regression plots presented here suggested that higher risk firms were more likely to be approved in such low interest rate prefectures, which implied the occurrence of adverse selection, even worse than a pooling equilibrium. By contrast, in high interest rate prefectures, approvals were consistently more likely for lower risk firms, suggesting that banks did costly screening and that their lending decisions were more appropriately aligned with borrower risk.

4.4 Estimation on Bank Characteristics

Table 7 showed that lending distortion worsens with weak bank balance sheet. The regression here includes banks' nonperforming loan (NPL) ratio and capital adequacy ratio as explanatory variables. Because these variables were included, this specification excluded the main bank fixed effects. The estimated coefficient on the NPL ratio was

significantly positive, and that on the capital adequacy ratio was significantly negative. These results suggested that main banks with higher NPL ratios or lower capital adequacy ratios before COVID-19 were more active in extending zero-zero loans. This pattern pointed to the possibility of lender-side moral hazard in the zero-zero loan program. Given the combination of a 100% public loan guarantee and full reimbursement of interest payments, zero-zero loans involved relatively low risk for lenders. As a result, banks with weaker balance sheets, which would otherwise have been less likely to take on risk, may have exploited the bad design of the program to expand lending through zero-zero loans.

Table 7: Estimation Results of Financial Institutions Operating in Multiple Prefectures

	(1)	(2)	(3)	(4)	(5)	(6)
	bank approve	bank approve	bank approve	bank approve	bank approve	bank approve
Interest Rate	0.023	1.097**	1.252***	1.255***	1.280***	0.965*
	(0.072)	(0.447)	(0.418)	(0.416)	(0.425)	(0.553)
Defaultscore_2019	0.032	3.094**	3.686***	3.585***	3.908***	3.799***
	(0.347)	(1.383)	(1.274)	(1.321)	(1.299)	(1.324)
Interest Rate * Defaultscore_2019		-2.243**	-2.681***	-2.609***	-2.765***	-2.675***
		(0.972)	(0.896)	(0.929)	(0.913)	(0.930)
Cash-to-Assets_2019	-0.111	-0.120	-0.115	-0.113	-0.083	-0.076
	(0.144)	(0.142)	(0.146)	(0.146)	(0.149)	(0.149)
CurrentAssets_2019	0.051	0.059	-0.021	-0.021	-0.042	-0.050
	(0.103)	(0.103)	(0.105)	(0.105)	(0.104)	(0.105)
Sales_2019	-0.022	-0.028	-0.032	-0.033	-0.027	-0.027
	(0.027)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)
Employees_2019	-0.002	0.000	0.009	0.010	0.003	0.003
	(0.027)	(0.026)	(0.026)	(0.026)	(0.027)	(0.027)
2016-2018 bank NPL ratio			0.038***	0.068		
			(0.013)	(0.060)		
interest rate * 2016-2018 bank NPL ratio				-0.021		
				(0.042)		
2016-2018 bank capital ratio					-0.012*	-0.045
					(0.007)	(0.033)
interest rate * 2016-2018 bank capital ratio						0.024
						(0.024)
Observations	1301	1301	1313	1313	1319	1319
Interest Rate Setting	Median	Median	Median	Median	Median	Median
Industry FE	YES	YES	YES	YES	YES	YES

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: Robust standard errors clustered at the prefectureindustry level are reported in parentheses, where industries are defined at the three-digit level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

5 Robustness Check 1

Prefectural interest rate criteria differed across prefectures: in some prefectures, interest rates were uniquely fixed, whereas in others only an upper bound was imposed, which allowed banks to flexibly set interest rates within the caps depending on borrowers.

This is especially important to enable banks to offer multiple loan contracts to achieve a separating equilibrium if adverse selection is the potential distortion. In this section, we analyzed whether such differences in the flexibility of prefectural interest rate criteria affected the lending behavior of banks operating in multiple prefectures.

Table 8: Estimation Results of Financial Institutions Operating in Prefectures with Fixed Interest Rate

	(1)	(2)	(3)
	bank approve	bank approve	bank approve
Interest Rate	0.087	0.111	-2.459
	(0.205)	(0.793)	(4.581)
Defaultscore_2019	-0.220	-0.156	-2.816
	(0.798)	(2.507)	(7.040)
Interest Rate * Defaultscore_2019		-0.050	4.472
		(1.842)	(10.687)
Interest Rate^2			1.020
			(1.742)
Interst Rate$^2 * Defaultscore_2019$			-1.789
			(3.964)
Cash-to-Assets_2019	0.090	0.090	0.101
	(0.261)	(0.262)	(0.264)
CurrentAssets_2019	-0.226	-0.225	-0.233
	(0.203)	(0.203)	(0.203)
Sales_2019	0.009	0.009	0.010
	(0.052)	(0.052)	(0.052)
Employees_2019	-0.108*	-0.109*	-0.108*
	(0.058)	(0.058)	(0.058)
Observations	391	391	391
Interest Rate Setting	Median	Median	Median
Industry FE	YES	YES	YES
Mainbank FE	YES	YES	YES

Notes: Robust standard errors clustered at the prefectureindustry level are reported in parentheses, where industries are defined at the three-digit level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

We found flexibility of contracts was important. Tables 8 and 9 reported the estimation results. Table 8 presented the results of estimations using firms located in prefectures where interest rates were uniquely fixed, while Table 9 presented the results of the estimations using firms firms located in prefectures where an interest rate cap was imposed. In Table 8, neither the estimated coefficient on the interest rate nor the estimated coefficient on the interaction between the interest rate and the default score was statistically significant. In contrast, in Table 9, the estimated coefficient on the interest rate was

significantly positive, while the estimated coefficient on the interaction between the interest rate and the default score was significantly negative, which were consistent with the findings in the previous section.

Table 9: Estimation Results of Financial Institutions Operating in Prefecture with Interest Rate Caps

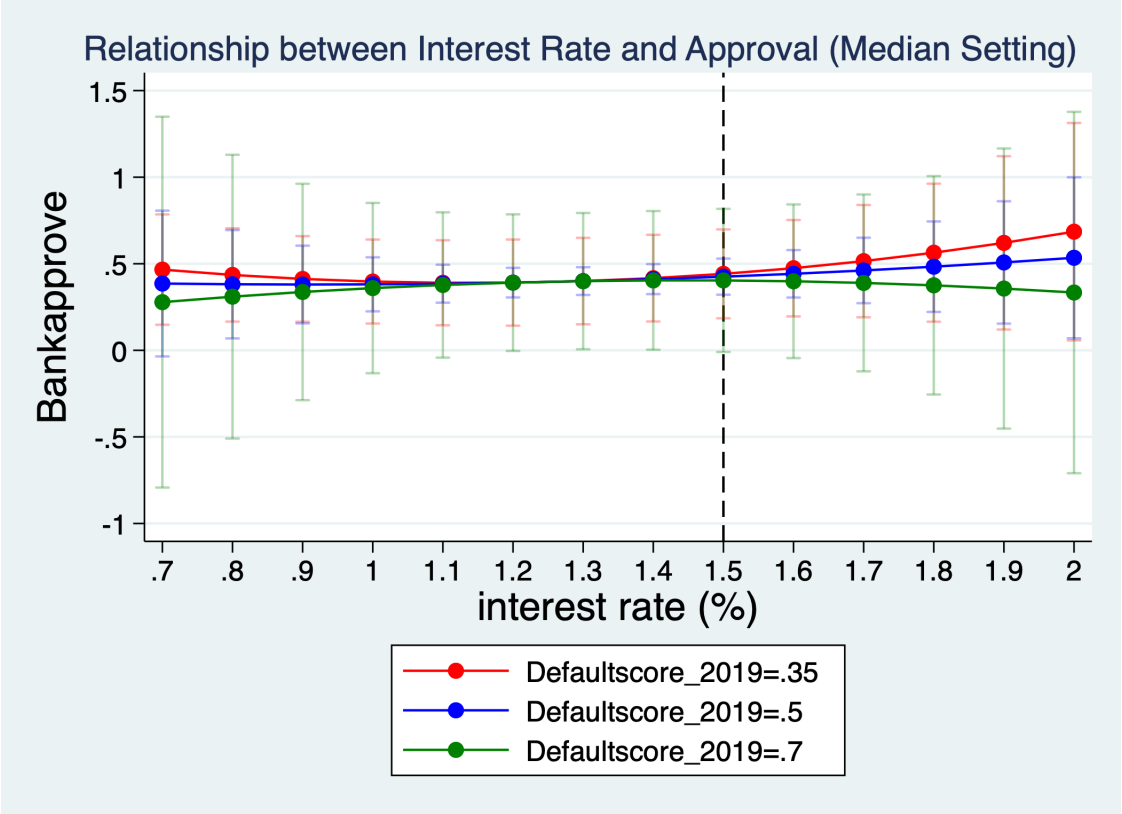
	(1)	(2)	(3)
	bank approve	bank approve	bank approve
Interest Rate	0.060	1.225*	-1.136
	(0.124)	(0.631)	(6.563)
Defaultscore_2019	0.265	3.609*	-3.676
	(0.460)	(1.964)	(9.817)
Interest Rate * Defaultscore_2019		-2.411*	7.656
		(1.354)	(13.859)
Interest Rate^2			0.814
			(2.270)
Interst Rate$^2 * Defaultscore$_2019			-3.412
			(4.781)
Cash-to-Assets_2019	-0.115	-0.120	-0.120
	(0.208)	(0.206)	(0.203)
CurrentAssets_2019	0.115	0.118	0.123
	(0.133)	(0.133)	(0.131)
Sales_2019	-0.020	-0.030	-0.034
	(0.032)	(0.029)	(0.029)
Employees_2019	0.020	0.024	0.024
	(0.034)	(0.033)	(0.032)
Observations	823	823	823
Interest Rate Setting	Median	Median	Median
Industry FE	YES	YES	YES
Mainbank FE	YES	YES	YES

Notes: Robust standard errors clustered at the prefectureindustry level are reported in parentheses, where industries are defined at the three-digit level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Figure 13 and 14 illustrated the relationships between approval of zero-zero loans and prefectural interest rates. They followed the same approach as in the previous section. In each figure, the horizontal axis represented the interest rate, and the vertical axis represented the fitted value of bankapprove from the specification in column (3), plotted separately for different levels of borrower default risk. Figure 13 showed that in prefectures where interest rates were uniquely fixed, lending behavior did not differ by borrowers' risk, regardless of whether the prefectural interest rate level was low or high. By contrast, Figure 14 showed that in prefectures where an interest rate cap was imposed,

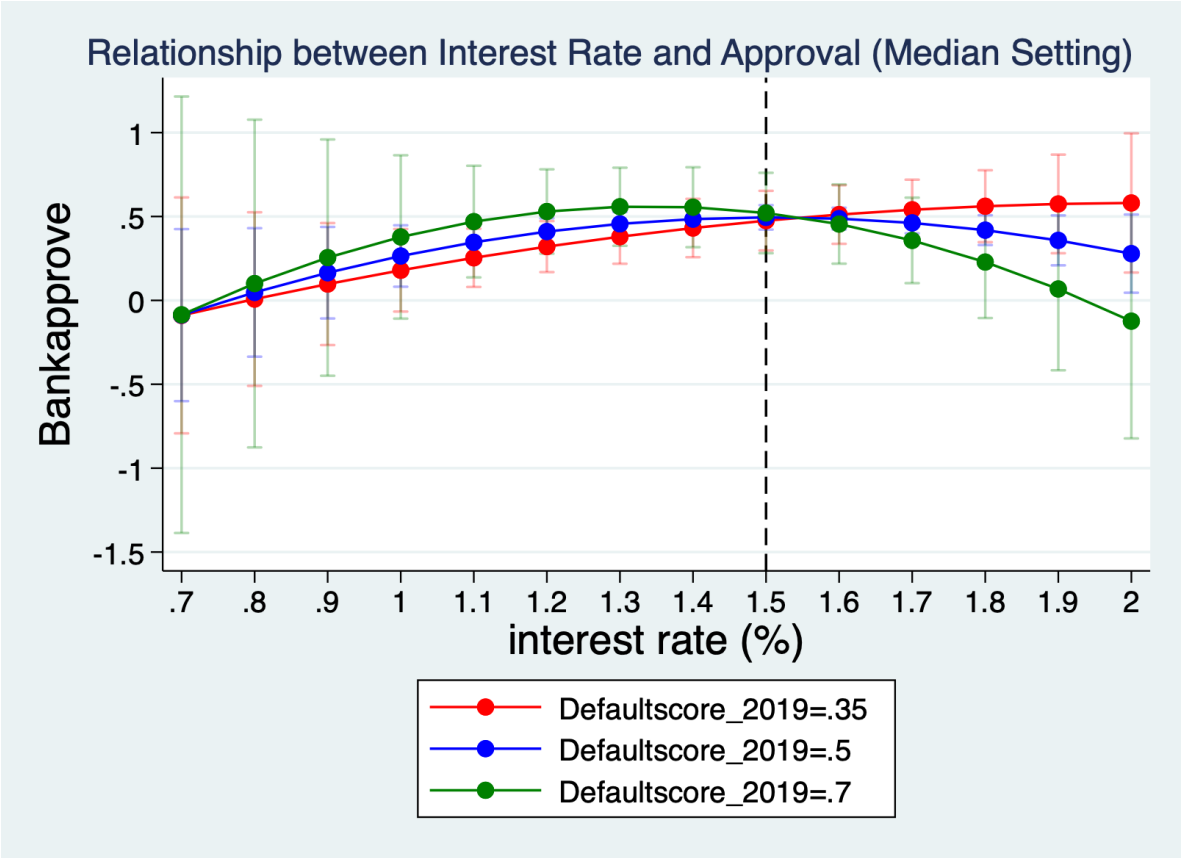
although the tendency was weaker than that observed in the previous section, financial institutions were more likely to extend zero-zero loans to borrowers with low default risk than to those with high default risk when prefectural interest rates were sufficiently high. In prefectures with lower interest rates, however, no statistically significant difference in lending behavior by borrowers' default risk was observed.

Figure 13: Relationship between Approval and Interest Rates: Cases of Prefectures with Fixed Rate



Taken together, these results indicated that the findings in the previous section may be derived from differences in prefectural interest rate criteria. Even among banks operating across multiple prefectures, the differential lending behavior emerged mainly in prefectures where interest rate caps allowed flexibility in interest rate level. In prefectures with uniquely fixed interest rates, financial institutions were unable to change interest rates across borrowers and therefore could not offer multiple contracts. As a result, lending outcomes reflected a pooling equilibrium even in prefectures with high interest rates. In contrast, in prefectures with interest rate caps, financial institutions could adjust interest rates across borrowers and thus offer different contracts depending on borrower

Figure 14: Relationship between Approval and Interest Rates: Cases of Prefectures with Caps



type. Thus, in prefectures with high interest rates, financial institutions engaged in costly screening and/or offered self-selection contracts to extend loans to low risk firms, which led to a separating equilibrium.

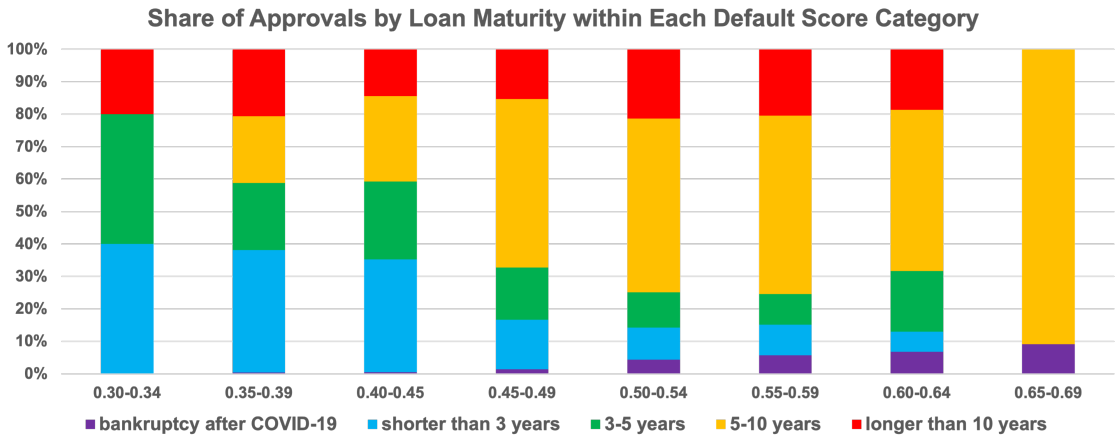
6 Robustness Check 2

In this section, we analyzed bank lending behavior under the zero-zero loan program by focusing on loan maturity to examine how financial institutions adjusted loan durations in response to prefectural interest rates and borrower types. It is well known that, for risky borrowers, investors tend to lend only in short-term bonds. Hence, separating equilibrium may occur relating to maturity choice. Therefore, it is essential to assess banks' behavior under the zero-zero loan program not only examining whether loans were approved, but also loan maturity.

We use data from the survey conducted in May 2024. While the earlier analyses relied on survey data collected in both 2021 and 2024, questions regarding loan maturity are included only in the 2024 survey. Therefore, this analysis is based on firms that responded to the 2024 survey and actually received zero-zero loans.

Figure 15 illustrates the relationship between borrower default risk and loan maturity among firms that received zero-zero loans. Default risk is measured using the default score employed in the previous analyses, and firms are grouped into bins ranging from 0.3 to 0.7 in increments of 0.05. Loan maturity is measured using survey responses, which classify loan terms into four categories: less than three years, three to five years, five to ten years, and more than ten years. For each default score bin, we calculate the share of firms in each maturity category and plot these distributions.

Figure 15: Share of Approvals by Loan Maturity within Default Score



In addition, we incorporated bankruptcy information from TSR's bankruptcy database and computed post-COVID-19 bankruptcy rates for firms within each default score bin. These bankruptcy rates were added to the figure. The sample used here consisted only of firms that responded to the 2024 survey and thus survived from the COVID-19 pandemic until the time of the survey. As a result, firms that went bankrupt during the four years between receiving zero-zero loans and the survey date were not observed in the sample. This attrition was likely to be more pronounced among firms with higher default score and shorter loan maturities. By incorporating bankruptcy rates by default score bin, we aimed to partially address this survivor-ship bias.

Examining the figure, the relationship between loan maturity under the zero-zero loan program and the default score appeared opposite to the usual relationship between firm risk and loan maturity. While bankruptcy rates clearly increased as the default score increased, long-term loans nevertheless accounted for a larger share among firms with higher default risk, even after taking bankruptcy rates into account. At the same time, the share of short-term loans also increased as the default score got lower. Under the full information situation, it would be rational for lenders to extend shorter-term loans to high risk borrowers and longer-term loans to low risk borrowers. The observed pattern therefore ran counter to this theoretical one, suggesting that even more adverse selection with respect to loan maturity may have arisen under the zero-zero loan program.

To further investigate the relationship between loan maturity, prefectural interest rates, and borrower default risk, we conduct the following regression. The sample consists of firms from the 2024 survey that received zero-zero loans and reported loan maturity information. As in the benchmark analysis, we conduct separate analyses for banks operating in only one prefecture and for those operating across multiple prefectures.

We employ an ordered logit model, as loan maturity was measured as an ordered categorical variable with four levels, ranging from less than three years to more than ten years. The explanatory variables include prefectural interest rates under the zero-zero loan program, borrowers' default scores, and their interaction term. Control variables are the same as in the previous analyses and include pre-pandemic sales, employment, cash holdings, and the ratio of liquid assets. Instead of fixed effects, we included industry dummy variables to control for industry heterogeneity. The regression specification was as follows.

$$y_i^* = X_{i,k}'\beta + Z_i'\theta + \varepsilon_i,$$

where the observed outcome y_i is defined as

$$y_i = m \quad \text{if} \quad \kappa_{m-1} < y_i^* \leq \kappa_m, \quad m = 1, \ldots, 4,$$

and ε_i follows a standard logistic distribution. The dependent variable y_i represents the loan maturity category reported in the survey, where higher values correspond to longer loan maturities. The vector X_i includes the prefectural interest rate, the default score of firm i, and the interaction term between the interest rate and the default risk. The vector Z_i contains the control variables and industry dummy variables explained above.

Table 10: Estimation Results of Loan Maturity

	(1) Maturity	(2) Maturity	(3) Maturity	(4) Maturity
Interest Rate	-0.188	62.450*	0.120	11.701*
	(3.229)	(33.293)	(0.648)	(6.445)
Defaultscore_2019	43.791**	205.903**	12.200***	45.552**
	(18.888)	(97.431)	(4.049)	(18.892)
Interest Rate * Defaultscore_2019		-125.788**		-24.486*
		(63.400)		(13.464)
2016-2018 bank NPL ratio	-1.142	-0.809	0.111	0.109
	(0.921)	(1.042)	(0.121)	(0.120)
Cash-to-Assets_2019	-12.383	-13.857	-0.189	-0.127
	(8.935)	(10.678)	(1.047)	(1.042)
CurrentAssets_2019	0.348	-1.888	0.237	0.446
	(7.383)	(10.553)	(0.995)	(0.984)
Sales_2019	-2.062	-2.967	-0.072	-0.097
	(2.936)	(4.010)	(0.254)	(0.258)
Employees_2019	3.646	4.429	-0.055	-0.033
	(4.195)	(5.748)	(0.265)	(0.271)
Observations	50	50	238	238

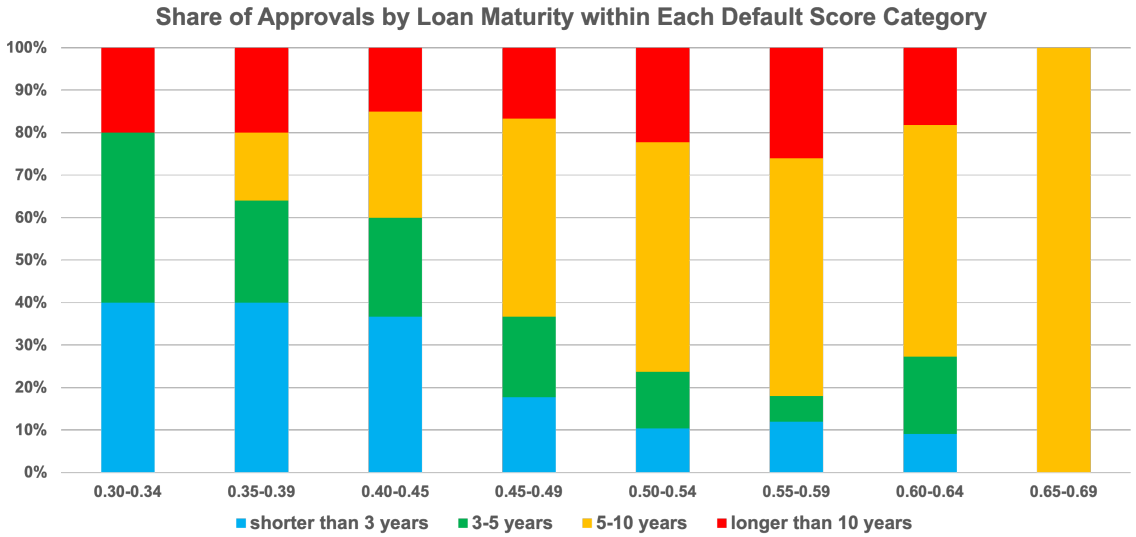
Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 10 reported the estimation results. Columns (1) and (2) presented results for the sample of financial institutions operating in only one prefecture, while columns (3) and (4) presented results for institutions operating across multiple prefectures. Columns (1) and (3) excluded the interaction term, whereas columns (2) and (4) included it.

In columns (1) and (3), the estimated coefficient on the default score was significantly positive, indicating that firms with higher default risk tended to receive longer-term loans. This finding was consistent with the patterns observed in Figure 10. In columns (2) and (4), the estimated coefficients on both the interest rate and the default score were significantly positive, while the estimated coefficient on the interaction term was significantly negative in both cases. These results indicated that, on average, longer-term zero-zero loans were extended in prefectures with higher interest rates.

Figure 16: Share of Approvals by Loan Maturity within Default Score (less than 1.5%)

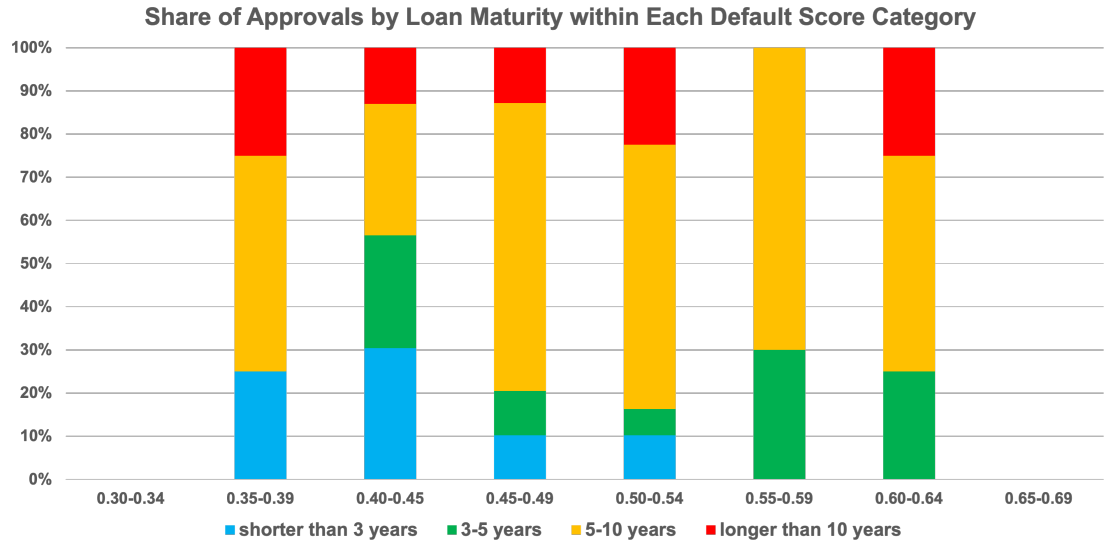


At the same time, as borrower default risk increased, in prefectures with higher interest rates, zero-zero loans were more likely to be shorter-term loans. Since it was generally rational for lenders to extend shorter-term loans to high risk borrowers and longer-term loans to low risk borrowers, these findings suggested that in prefectures with higher interest rates, financial institutions set loan maturities more appropriately.

Figure 16 and 17 further illustrated these relationships by splitting samples used in Figure 15 into two subsamples based on prefectural interest rates. We set the cutoff at 1.5%: Figure 16 used the sample of prefectures with interest rates below 1.5%, while Figure 17 used the sample of prefectures with interest rates of 1.5% or higher. Figure 16 showed a pattern similar to that in Figure 15, where firms with higher default scores had a larger share of long-term loans, while firms with lower default scores had a larger share of relatively short-term loans of five years or less. In contrast, Figure 17 showed a larger share of long-term loans among firms with low default risk. These patterns were consistent with the regression results. For firms with high default risk, however, differences in loan maturity across interest rate regimes were less pronounced.

Overall, the analysis of loan maturity under the zero-zero loan program suggested that adverse selection was prevalent. Firms with higher default risk tended to receive longer-term loans, contrary to what would be expected under rational lending behavior.

Figure 17: Share of Approvals by Loan Maturity within Default Score (1.5% or higher)



In contrast, in prefectures with higher interest rates, the correlation between default risk and loan maturity weakened regardless of the size of the lending institution. This pattern suggested that in high interest rate prefectures, financial institutions conducted stricter screening of borrowers and adopted more appropriate lending behavior. Nevertheless, even in high interest rate prefectures, lending behavior was not fully consistent with optimal screening, and distortions in credit allocation could not be ruled out.

7 Conclusion

We found strong evidence of moral hazard in bank behavior using a unique natural experiment in Japan during the COVID-19 pandemic. Specifically, exogenous variations in loan rates under a free lunch like government loan program occurred randomly across 47 prefectures. While it was intended to save viable SMEs at the time, the policy was poorly designed - that is our evaluation.

First, we found clear evidence of moral hazard. For banks with operations across multiple prefectures, loan growth is higher in prefectures with higher loan rate limits; by contrast, there is no such tendency among banks operating only in one prefecture.

Second, we found evidence of costly screening behavior. In a prefecture with a low loan rate limit, banks tend to select bad firms more than good firms. By contrast, in a prefecture with a high loan rate limit, banks tend to select good firms more than bad firms. These two opposite behaviors are consistent with the costly screening hypothesis, which holds that screening occurs only if the benefits exceed the cost; otherwise, pooling occurs.

This within-prefecture behavior somewhat mitigates the across-prefecture moral hazard. Banks move their funds to high interest rate prefectures, where they select good firms. Still, the overall picture shows that banks increased loans to bad firms. Thus, this mitigating effect is not enough to cancel the moral hazard created by the new government policy.

References

Gao, Y. and K. Ueda (2025). Loan screening under symmetrically imperfect information. Technical report, Center for Advanced Research in Finance, Faculty of Economics, The .

Hoshi, T., D. Kawaguchi, and K. Ueda (2023). Zombies, again? the covid-19 business support programs in japan. *Journal of Banking & Finance 147*, 106421.

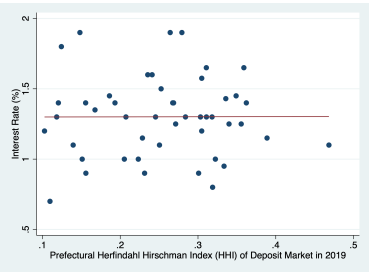
Uesugi, I., K. Hiraga, M. Manabe, and N. Yoshino (2024). Koronaka no motode no chiiki kinyuu shizyo: Syuuchudo, kashidashi, yokin wo tsuujita chiikikan shikin jyunkan, shinyou hosyo tsuki kashidashi (regional financial markets during covid-19 pandemic: Concentration, inter-regional flow of funds via loans and deposits, and credit guaranteed loans). *Financial Research Center Discussion Paper DP2024-2*.

Appendix

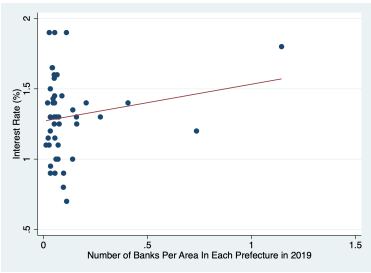
A1: Confirmation of Correlation between Prefectural Interest Rates and Economic Measures

In this section, we examine the correlations between the interest rates on the zero-zero loan program set for each prefecture and other economic measures and show that the interest rates on the zero-zero loan were determined independently of the economic scale and financial demand of each prefecture. Figure 18 presents the correlations between prefecture-level Zero-Zero Loan interest rates and indicators of local deposit market structure, such as the Herfindahl-Hirschman Index (HHI), the number of bank branches per unit of area, and the number of bank branches per capita. We use data from the Cabinet Office's System of Natural Accounts for prefectural population figures, data from the Geospatial Information Authority of Japan for prefectural area figures, and data from "Nihon Kinyu Meikan" in 2019 for the number of financial institutions in each prefecture. Table 11 reports the results of simple regression analyses to check whether these correlations are statistically significant. As shown in the table, none of these financial market indicators is significantly correlated with the prefectural interest rates.

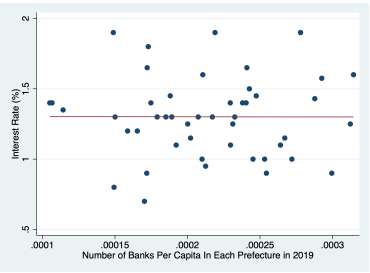
Figure 18: Correlation between Prefectural Interest Rate and Financial Situations



HHI in Deposit Market



Number of Banks Per Area



Number of Banks Per Capita

Next, Figure 19 illustrates the correlations between the prefectural shares of secondary and tertiary industries in all industries, and the prefectural interest rates.[19] The industrial composition ratios for each prefecture are calculated as averages over the ten-year period

[19]The definitions of secondary and tertiary industries follow the Japanese Standard Industrial Classification.

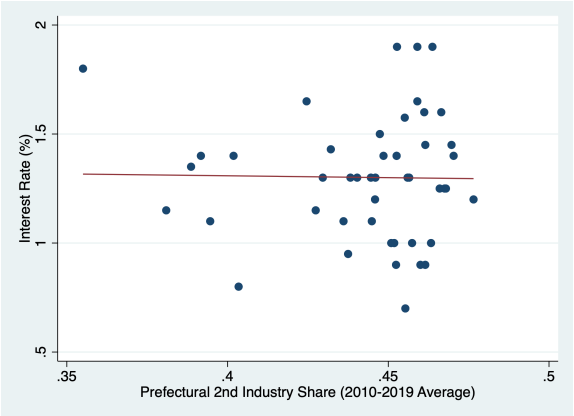
Table 11: simple regression about measures related to financial situation

	(1) Interest Rate	(2) Interest Rate	(3) Interest Rate
HHI deposit market	0.009		
	(0.502)		
Banks per area		0.262	
		(0.216)	
Banks per capita			-12.978
			(818.117)
Observations	47	47	47
Interest Rate Setting	Median	Median	Median

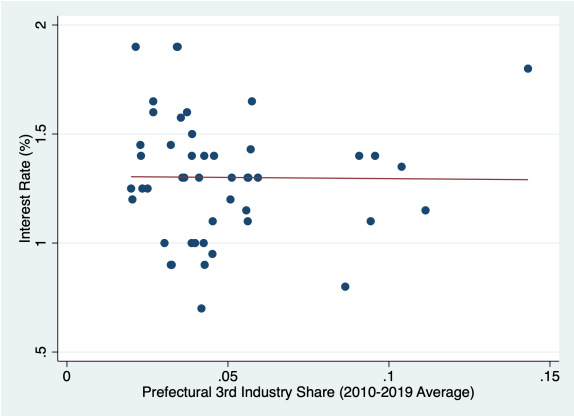
Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Figure 19: Correlation between Prefectural Interest Rate and Industry Share



2nd Industry Share



3rd Industry Share

from 2010 to 2019, using the full sample of the firm-level credit research report produced by Tokyo Shoko Research. Table 12 shows whether these correlations are significantly correlated using simple regression analyses. Again, there is no significant correlation between the industrial ratios for each prefecture and the prefectural interest rate on the zero-zero loan.

Figures 20 show the correlations between average firm sales and EBIT (earnings before interest and taxes) at the prefectural level and the prefectural interest rates. Both of them are calculated using the same methodology as that employed for industrial composition. Table 13 reports the results of simple regression analyses assessing the statistical significance of these correlations. As can be seen in the left hand side of Figure 20, there is a single outlier in the upper-right corner of the plot, corresponding to Tokyo. As a

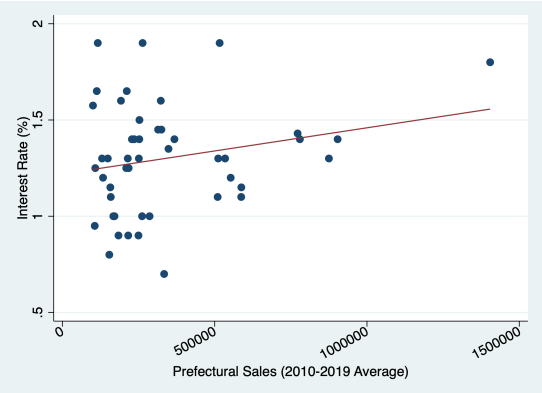
Table 12: simple regression about prefectural industrial ratio

	(1) Interest Rate	(2) Interest Rate
2nd Industry Share	-0.172	
	(1.597)	
3rd Industry Share		-0.111
		(1.602)
Observations	47	47
Interest Rate Setting	Median	Median

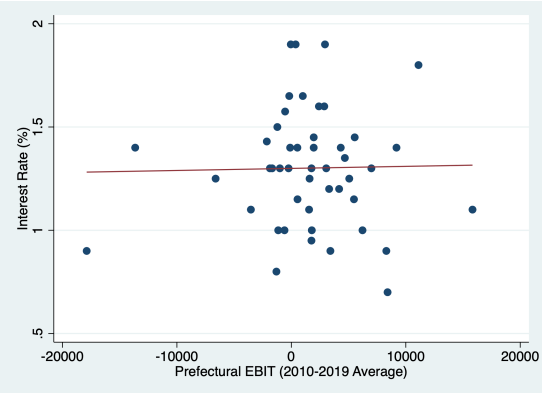
Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Figure 20: Correlation between Prefectural Interest Rate and Sales/EBIT



10-Years Average of Sales



10-Years Average of EBIT

result, the relationship between average sales and interest rates appears to be positive. However, we find that there is no significant correlation between prefectural average sales and prefectural interest rates as well as prefectural average EBIT.

A2: Robustness Check 3

In the benchmark estimations, we analyzed the data using the median interest rate representation. In this section, we conducted robustness checks using high and low interest rate representations. As in the benchmark analysis, we used pre-pandemic sales and employment as control variables. The sample was also restricted to firms whose maximum monthly sales decline immediately after the pandemic was 15% or more, focusing on loans with 100% loan guarantees and full interest reimbursement. The estimation strategy followed the benchmark specification and employed fixed-effects models. All explanatory

Table 13: simple regression about firm sales and EBIT

	(1) Interest Rate	(2) Interest Rate
10-years Averaged Sales	0.000	
	(0.000)	
10-years Averaged EBIT		0.000
		(0.000)
Observations	47	47
Interest Rate Setting	Median	Median

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

variables other than the prefectural interest rate, including the control variables, were same as those used in the benchmark estimations.

We first examined the case of the high interest rate representation. Tables 14 and 15 report the estimation results. Table 14 presents the results for financial institutions that operate in only one prefecture, while Table 15 reports the results for financial institutions in multiple prefectures. In both tables, column (1) reports estimates without interaction terms, column (2) adds the interaction between the interest rate and the default score, and column (3) further includes the squared interest rate term along with the interaction term. In Table 14, none of the estimated coefficients on the interest rate, the default score, or their interaction were statistically significant across all specifications. This result indicated that, for financial institutions operating in only one prefecture, lending behavior under the zero-zero loan program did not vary systematically with the prefectural interest rate, which was consistent with the benchmark findings.

Next, we checked results in Table 15. In column (1), none of the coefficients were statistically significant. In column (2), however, the coefficient on the interest rate was significantly positive, the coefficient on the default score was also significantly positive, and the coefficient on the interaction between the default score and the interest rate was significantly negative. These results were fully consistent with those obtained in the benchmark estimation. In column (3), although the coefficients in rows 1 through 3 differed from the benchmark results, the coefficient on the squared interest rate was significantly positive and the coefficient on the interaction term between the default

Table 14: Estimation Results of Financial Institutions Operating in A Single Prefecture

	(1)	(2)	(3)
	bank approve	bank approve	bank approve
Interest Rate	0.050	-0.494	8.271
	(0.164)	(1.065)	(7.254)
Defaultscore_2019	0.184	-1.286	8.283
	(0.843)	(3.066)	(10.234)
Interest Rate * Defaultscore_2019		1.104	-13.373
		(2.222)	(14.946)
Interest Rate^2			-3.131
			(2.587)
Interst Rate$^2 * Defaultscore$_2019			5.197
			(5.313)
Cash-to-Assets_2019	-0.113	-0.118	-0.149
	(0.378)	(0.382)	(0.398)
CurrentAssets_2019	0.087	0.090	0.149
	(0.268)	(0.268)	(0.267)
Sales_2019	0.069	0.068	0.069
	(0.073)	(0.073)	(0.073)
Employees_2019	-0.138	-0.134	-0.134
	(0.088)	(0.088)	(0.088)
Observations	225	225	225
Interest Rate Setting	High	High	High
Industry FE	YES	YES	YES
Mainbank FE	YES	YES	YES

Notes: Robust standard errors clustered at the prefectureindustry level are reported in parentheses, where industries are defined at the three-digit level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

score and the square term was significantly negative, which were also consistent with the benchmark findings.

Figure 21 illustrated the relationship between prefectural interest rates and the probability of zero-zero loan approval by default risk, using the fitted values of the dependent variable from column (3). Similar to Figure 11, the figure showed that for low risk borrowers, the relationship between the approval and the interest rate was upward sloping. As borrower risk increased, the slope gradually turned downward, and for high risk borrowers the relationship became clearly downward sloping. Moreover, in prefectures with sufficiently high interest rates, zero-zero loans were significantly more likely to be extended to low risk borrowers than to high risk borrowers, whereas in prefectures with relatively low interest rates, no significant differences were observed across borrower risk

Table 15: Estimation Results of Financial Institutions Operating in Multiple Prefectures

	(1) bank approve	(2) bank approve	(3) bank approve
Interest Rate	0.034	0.956***	-5.405**
	(0.059)	(0.368)	(2.357)
Defaultscore_2019	0.020	2.798**	-7.446**
	(0.347)	(1.213)	(3.755)
Interest Rate * Defaultscore_2019		-1.925**	12.396**
		(0.796)	(5.249)
Interest Rate^2			2.123***
			(0.812)
Interst Rate$^2 * Defaultscore$_2019			-4.757***
			(1.781)
Cash-to-Assets_2019	-0.110	-0.119	-0.110
	(0.143)	(0.142)	(0.141)
CurrentAssets_2019	0.050	0.059	0.046
	(0.103)	(0.103)	(0.101)
Sales_2019	-0.023	-0.031	-0.035
	(0.027)	(0.024)	(0.023)
Employees_2019	-0.002	0.001	0.005
	(0.027)	(0.026)	(0.025)
Observations	1301	1301	1301
Interest Rate Setting	High	High	High
Industry FE	YES	YES	YES
Mainbank FE	YES	YES	YES

Notes: Robust standard errors clustered at the prefectureindustry level are reported in parentheses, where industries are defined at the three-digit level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

levels. These patterns were the same as those observed in Figure 11.

We next confirm the case of the low interest rate representation. Table 16 and 17 again report the estimation results, with Table 16 corresponding to financial institutions operating in only one prefecture and Table 17 corresponding to institutions operating in multiple prefectures. The specifications were identical to those used in the high rate setting case. Focusing first on Table 16, none of the coefficients on the interest rate, the default score, or their interaction were statistically significant across all columns, consistent with the benchmark results.

Next, in Table 17, column (1) showed no statistically significant coefficients. In column (2), however, the coefficient on the interest rate was significantly positive, the coefficient on the default score was significantly positive, and the coefficient on their interaction was

Table 16: Estimation Results of Financial Institutions Operating in A Single Prefecture

	(1) bank approve	(2) bank approve	(3) bank approve
Interest Rate	0.039	-0.383	5.490
	(0.190)	(1.320)	(8.862)
Defaultscore_2019	0.188	-0.796	4.917
	(0.854)	(3.261)	(10.667)
Interest Rate * Defaultscore_2019		0.848	-8.544
		(2.693)	(17.438)
Interest Rate^2			-2.307
			(3.531)
Interst Rate$^2 * Defaultscore$_2019			3.676
			(6.903)
Cash-to-Assets_2019	-0.104	-0.098	-0.112
	(0.373)	(0.375)	(0.388)
CurrentAssets_2019	0.088	0.085	0.091
	(0.272)	(0.274)	(0.275)
Sales_2019	0.070	0.070	0.074
	(0.074)	(0.075)	(0.076)
Employees_2019	-0.139	-0.137	-0.140
	(0.089)	(0.089)	(0.090)
Observations	225	225	225
Interest Rate Setting	Low	Low	Low
Industry FE	YES	YES	YES
Mainbank FE	YES	YES	YES

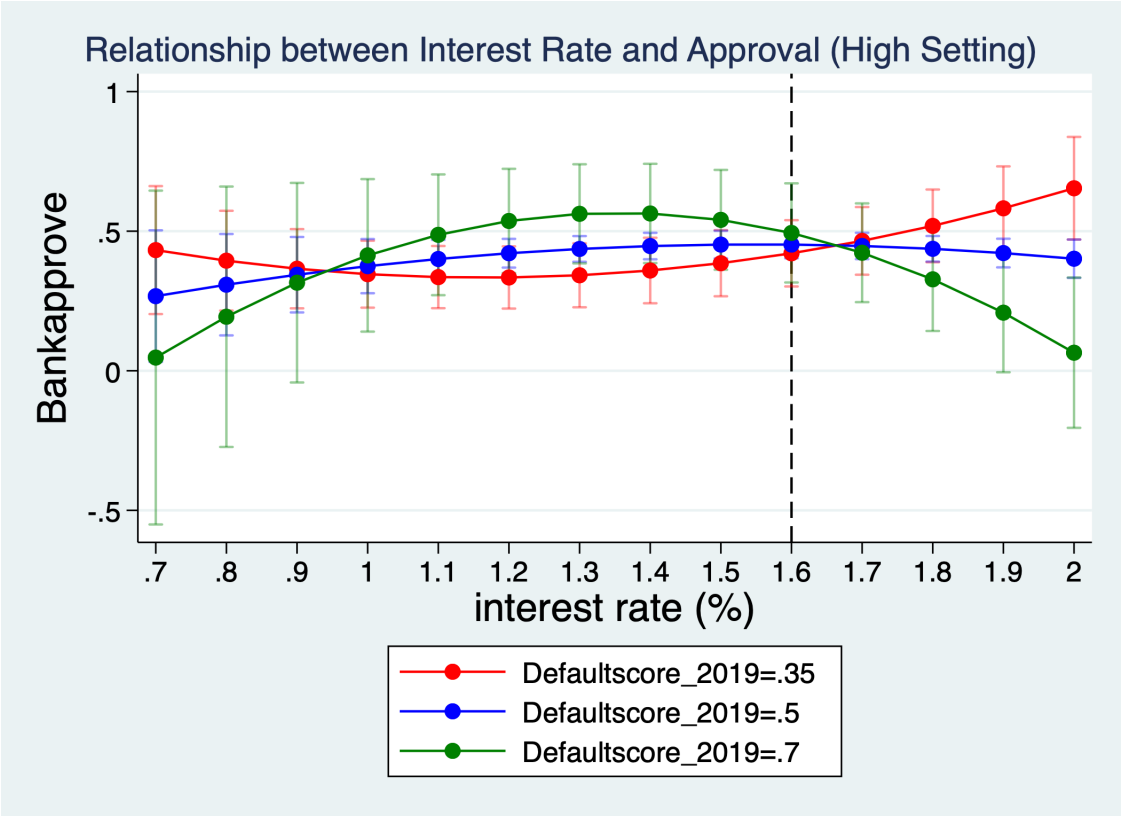
Notes: Robust standard errors clustered at the prefectureindustry level are reported in parentheses, where industries are defined at the three-digit level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 17: Estimation Results of Financial Institutions Operating in Multiple Prefectures

	(1) bank approve	(2) bank approve	(3) bank approve
Interest Rate	-0.004	0.979**	-2.253
	(0.085)	(0.490)	(2.837)
Defaultscore_2019	0.048	2.685*	-2.154
	(0.347)	(1.422)	(4.162)
Interest Rate * Defaultscore_2019		-2.051*	5.552
		(1.066)	(6.348)
Interest Rate^2			1.225
			(1.093)
Interst Rate$^2 * Defaultscore$_2019			-2.875
			(2.403)
Cash-to-Assets_2019	-0.112	-0.119	-0.122
	(0.143)	(0.142)	(0.143)
CurrentAssets_2019	0.052	0.057	0.057
	(0.103)	(0.104)	(0.103)
Sales_2019	-0.022	-0.024	-0.023
	(0.027)	(0.025)	(0.024)
Employees_2019	-0.003	-0.001	-0.002
	(0.027)	(0.026)	(0.026)
Observations	1301	1301	1301
Interest Rate Setting	Low	Low	Low
Industry FE	YES	YES	YES
Mainbank FE	YES	YES	YES

Notes: Robust standard errors clustered at the prefectureindustry level are reported in parentheses, where industries are defined at the three-digit level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

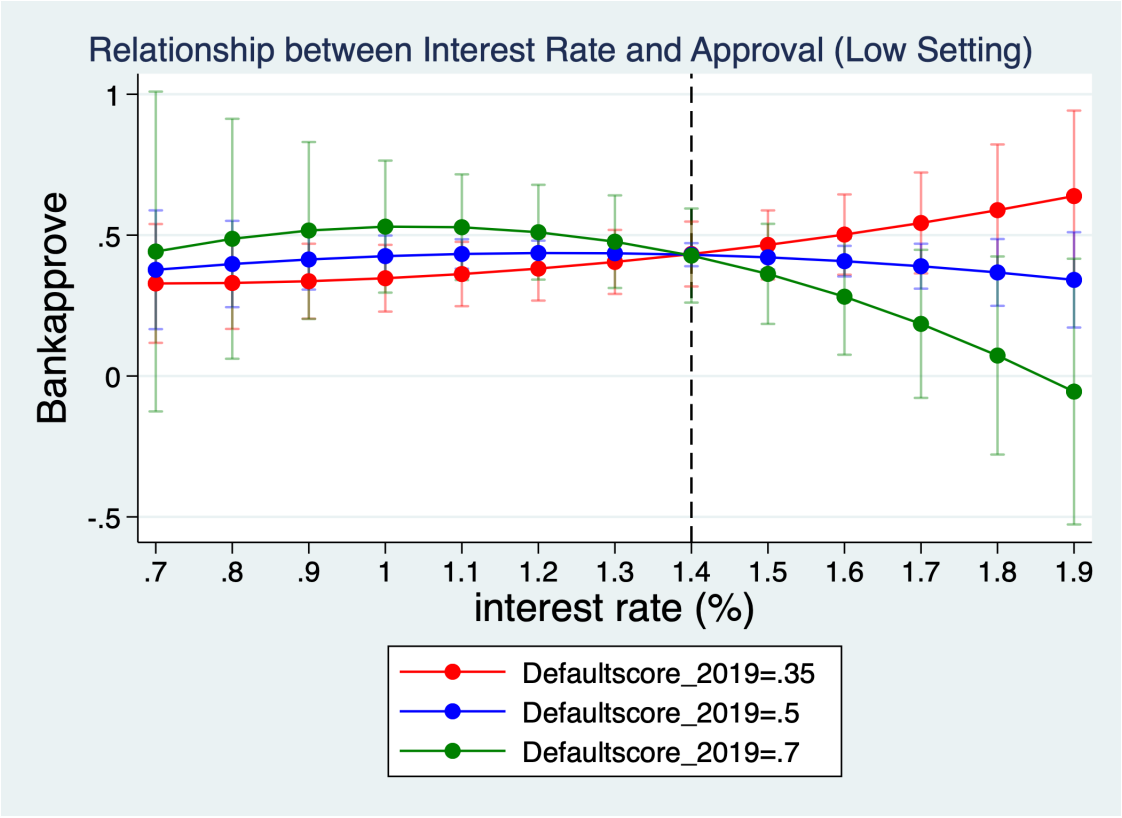
Figure 21: Relationship between Approval and Interest Rates



significantly negative, which were in line with the benchmark findings. In column (3), none of the coefficients were statistically significant. Figure 22 plotted the fitted values of the dependent variable from column (3) against the interest rate for different levels of default risk, in the same manner as Figure 21. Compared with Figure 16, the differences in approval behavior across borrower risk levels were less obvious even in prefectures with high interest rates. Nevertheless, as in Figure 11, the relationship was upward sloping in interest rates for low risk borrowers and downward sloping for high risk borrowers.

Taken together, these robustness checks indicated that using either high or low as the interest rate representation instead of the median representation did not change the main conclusions. Financial institutions operating in multiple prefectures tended to screen borrowers more appropriately and move toward separating equilibria in prefectures with high interest rates, while their incentives to screen were weaker in prefectures with low interest rates, resulting in pooling equilibria.

Figure 22: Relationship between Approval and Interest Rates



A3: Robustness Check 4

In the benchmark estimations, we employed linear regressions with industry fixed effects and main bank fixed effects. In this section, as a robustness check, we analyze the data using a nonlinear regression model based on a logit specification. As in the benchmark analysis, the sample was restricted to firms whose maximum monthly sales decline during the pandemic was 15% or more. Both the dependent variable and the explanatory variables are identical to those used in the fixed-effects specifications. Instead of industry fixed effects, we use industry dummy variables and main bank dummy variables to control for heterogeneity in industry and main bank. The regression model is specified as follows.

$$\Pr(y_i = 1 \mid X_{i,k}, Z_i) = \Lambda\left(X'_{i,k}\beta + Z'_i\theta\right),$$

where $\Lambda(\cdot)$ denotes the logistic cumulative distribution function. The dependent vari-

able y_i is a binary indicator equal to one if the loan application of firm i is approved and zero otherwise, same as the benchmark case. The vector X_i includes the main explanatory variables, and the vector Z_i contains control variables and dummy variables explained above.

Tables 18 and 19 were the results of nonlinear estimation. Table 18 showed the results for financial institutions operating in only one prefecture, while Table 19 showed the results for financial institutions operating in multiple prefectures. In both tables, column (1) reported estimates without interaction terms, column (2) included the interaction between the interest rate and the default score, and column (3) further added the squared interest rate term and the interaction term between the square term and the default score. We first examined Table 18. Across all columns, none of the estimated coefficients on the interest rate, the default score, or their interaction were statistically significant. This finding indicated that, for financial institutions operating in only one prefecture, lending behavior under the zero-zero loan program did not differ systematically with prefectural interest rates. This result was fully consistent with the benchmark estimations.

Next, we turned to Table 19. In column (1), none of the coefficients were statistically significant. In column (2), however, the coefficient on the interest rate was significantly positive, while the coefficient on the interaction between the default score and the interest rate was significantly negative. These results were again consistent with the benchmark findings. In column (3), the coefficient on the squared interest rate term was significantly positive, whereas the coefficient on the interaction between the square term and the default score was significantly negative. These results were also consistent with the benchmark estimations and suggested that, although banks extended more zero-zero loans in prefectures with higher interest rates, this tendency was weaker and finally became opposite for firms with higher default scores. Thus, the logit model analysis likewise indicated that banks became more cautious in lending to high risk firms in prefectures with high interest rates.

Figure 23 plotted the relationship between the fitted values of the dependent variable

Table 18: Estimation Results of Financial Institutions Operating in A Single Prefecture

	(1) bank approve	(2) bank approve	(3) bank approve
Interest Rate	0.232	-6.405	70.333
	(0.951)	(6.825)	(75.233)
Defaultscore_2019	0.695	-16.293	67.039
	(4.991)	(18.666)	(96.645)
Interest Rate * Defaultscore_2019		13.467	-116.256
		(14.111)	(145.575)
Interest Rate^2			-28.633
			(27.865)
Interst Rate$^2 * Defaultscore$_2019			48.365
			(53.870)
Cash-to-Assets_2019	-0.974	-1.044	-1.455
	(1.886)	(1.917)	(2.242)
Sales_2019	0.397	0.387	0.430
	(0.432)	(0.438)	(0.441)
Employees_2019	-0.928*	-0.923*	-0.976*
	(0.530)	(0.540)	(0.527)
Observations	174	174	174
Interest Rate Setting	Median	Median	Median

Notes: Robust standard errors clustered at the prefectureindustry level are reported in parentheses, where industries are defined at the three-digit level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

from column (3) and the prefectural interest rate for different levels of borrower default risk. The green line represented a low risk borrower with a default risk of 0.35, the blue line represented a medium-risk borrower with a default risk of 0.5, and the red line represented a high risk borrower with a default risk of 0.7. As shown in the figure, the relationship between interest rates and approval was upward sloping for low risk borrowers, whereas the slope gradually became negative as borrower risk increased, and it was clearly downward sloping for high risk borrowers. These patterns were consistent with the estimated coefficients on the squared interest rate term and the interaction with the default score. Moreover, in prefectures with sufficiently high interest rates, zero-zero loans were significantly more likely to be extended to low risk borrowers than to high risk borrowers. By contrast, in prefectures with relatively low interest rates, no statistically significant differences in approval were observed across borrower risk levels. Overall, these results were fully consistent with the benchmark findings. They indicated that banks operating in multiple prefectures screened borrowers more intensively and achieved separating

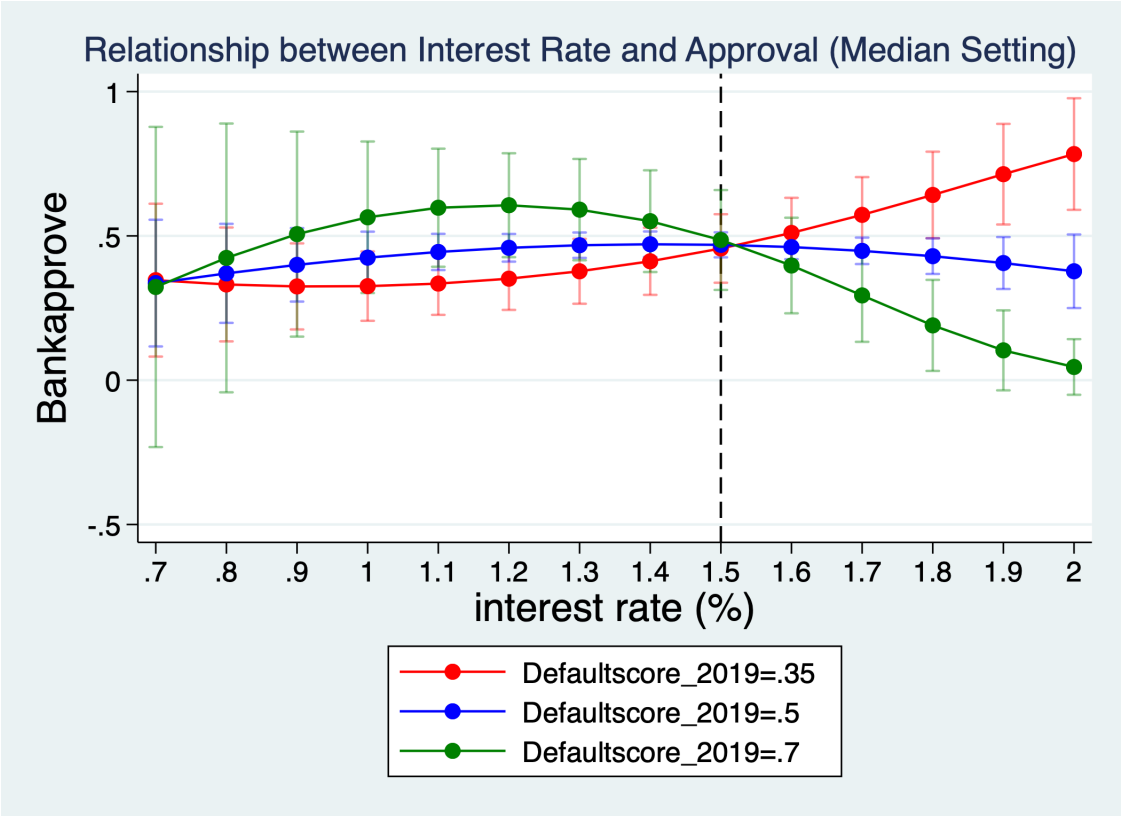
Table 19: Estimation Results of Financial Institutions Operating in Multiple Prefectures

	(1)	(2)	(3)
	bank approve	bank approve	bank approve
Interest Rate	0.152	7.731***	-24.574
	(0.387)	(2.530)	(16.863)
Defaultscore_2019	0.291	22.038***	-28.117
	(1.828)	(7.813)	(24.948)
Interest Rate * Defaultscore_2019		-15.621***	57.567
		(5.360)	(36.723)
Interest Rate^2			11.349*
			(6.105)
Interst Rate$^2 * Defaultscore$_2019			-25.680*
			(13.204)
Cash-to-Assets_2019	-0.445	-0.379	-0.367
	(0.736)	(0.739)	(0.730)
Sales_2019	-0.118	-0.167	-0.176
	(0.137)	(0.122)	(0.119)
Employees_2019	-0.047	-0.023	-0.012
	(0.141)	(0.137)	(0.136)
Observations	1166	1166	1166
Interest Rate Setting	Median	Median	Median

Notes: Robust standard errors clustered at the prefectureindustry level are reported in parentheses, where industries are defined at the three-digit level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

equilibria in prefectures with high interest rates, while weaker screening incentives in prefectures with high interest rates led to pooling equilibria, which may have given rise to adverse selection.

Figure 23: Relationship between Approval and Interest Rates



A4: Robustness Check 5

In this section, we use nonparametric local polynomial regression to examine the relationship between banks' lending behavior under the zero-zero loan program, prefectural interest rates, and borrowers' default risk, which provides supplementary evidence to the main estimation results. The analysis proceeds as follows. We first regress banks' approval decisions for zero-zero loans on factors other than prefecture-level interest rates and borrowers' default risk. We then examine the relationship between the residualized outcome variable obtained from this regression and prefectural interest rates as well as borrowers' default risk using local regression.

Specifically, we residualize the binary indicator for zero-zero loan approval using only control variables, excluding interest rates and default risk. We estimate the following fixed-effects model.

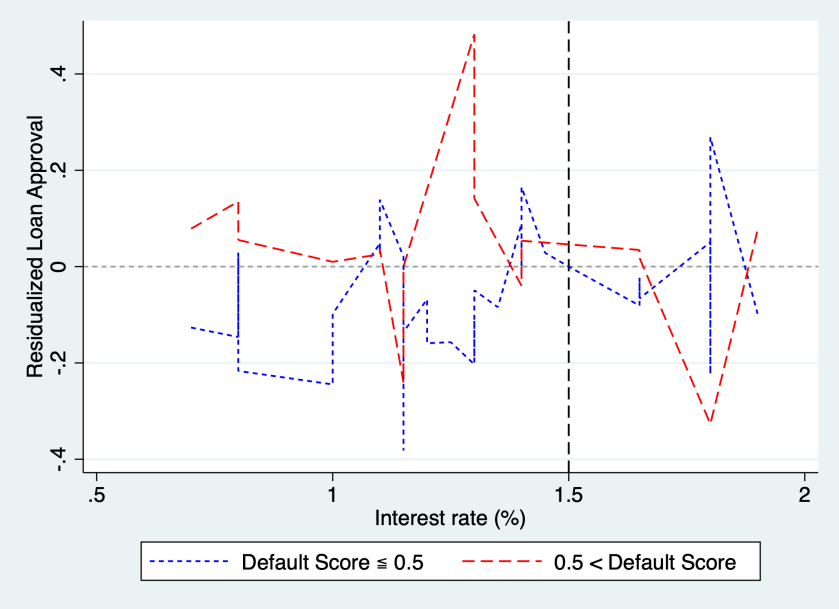
$$Y_{i,2020} = X'_{i,2019}\beta + Industry_j + MainBank_b + u_{i,2020}$$

As in the previous analysis, the dependent variable is a binary indicator equal to one if a firm's zero-zero loan application was approved. The vector $X_{i,2019}$ includes the same set of control variables used throughout the analysis, namely sales, the number of employees, the cash holding ratio, and the liquidity ratio of each firm in 2019. The term $Industry_j$ denotes industry fixed effects, and $MainBank_b$ denotes main bank fixed effects. We define the residuals obtained from this model as the residualized bank approval.

We then visualize the relationship between this variable and prefecture-level interest rates as well as borrowers' default risk using the nonparametric local regression. This visualization is not intended to estimate the effects of interest rates or default risk. Rather, it serves as a robustness check on the functional form in the parametric regression specifications used in the main analysis. Accordingly, the results presented in this section provide complementary evidence supporting the interpretation of the main findings regarding the impact of prefecture-level interest rates on banks' lending behavior under the zero-zero loan program and the relative differences associated with borrowers' default risk.

Figure 24 presented the local regression plots using samples whose main bank operated in a single prefecture. In the benchmark section, Figure 12 showed the corresponding plots using samples whose main bank operated in multiple prefectures, and indicated that in high interest rate prefectures, zero-zero loans were more extended to firms that were originally lower risk, whereas in other prefectures, they were more likely to extend zero-zero loans to firms with ex ante higher risk. As in Figure 12, Figure 24 divided the sample into two groups based on whether the default score was below or above 0.5 and plotted the relationships separately for each group. The figure showed that in prefectures with interest rates at or below 1.5%, there was a weak tendency for zero-zero loans to be extended more to firms with ex ante higher risk. However, compared with Figure 12, no

Figure 24: Relationship between Approval and Interest Rates Using Local Regression



Note: The figure plots locally weighted linear regressions estimated using a tri-cube kernel, as implemented by the "lowess" command in Stata, with a bandwidth of 0.05.

clear difference was observed in the relationship between prefectural interest rates and lending behavior by borrower risk. As reported in Table 6, we found that the lending behavior of financial institutions operating in a single prefecture was not significantly different by loan interest rates or default risk. The tendency observed in Figure 24 were broadly consistent with these results.